

1 **The predator activity landscape predicts the anti-predator behavior and distribution of**
2 **prey in a tundra community**

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12 **Abstract**

13 Predation shapes communities through consumptive and non-consumptive effects, where in the
14 latter prey respond to perceived predation risk through risk management strategies occurring at
15 different spatial and temporal scales. The landscape of fear concept is useful to better understand
16 how predation risk affects prey behavioral decisions and distribution, and more generally the
17 spatial dimension of predator-prey relationships. We assessed the effects of the predation risk
18 landscape in a terrestrial Arctic community, where arctic fox is the main predator of ground-
19 nesting bird species. Using high frequency GPS data, we developed a predator activity landscape
20 resulting from fox space use patterns, and validated with an artificial prey experiment that it
21 generated a predation risk landscape. We then investigated the effects of the fox activity
22 landscape on multiple prey, by assessing the anti-predator behavior of a primary prey (snow

23 goose) and the nest distribution of several incidental prey. Areas highly used by foxes were
24 associated with a stronger level of nest defense by snow geese. We further found a lower
25 probability of occurrence of incidental prey nests in areas highly used by foxes, but only for
26 species nesting in habitats easily accessible to foxes. Species nesting in refuges consisting of
27 micro-habitats limiting fox accessibility, like islets, did not respond to the fox activity landscape.
28 Consistent with the scale of the fox activity landscape, this result reflected the capacity of
29 refuges to allow bird nesting without regard to predation risk in the surrounding area. We
30 demonstrated the value of using predator space use patterns to infer spatial variation in predation
31 risk and better understand its effects on prey in landscape of fear studies. We also exposed the
32 diversity of prey risk management strategies, hence refining our understanding of the
33 mechanisms driving species distribution and community structure.

34 **Keywords:** anti-predator behavior, arctic fox, artificial prey experiment, landscape of fear, nest
35 distribution, predation risk, predator activity landscape, predator-prey interactions

36 **Introduction**

37 Predation plays a central role in ecological and evolutionary processes (Menge and Sutherland
38 1976, Ford et al. 2014). It shapes communities through both direct killing of prey (consumptive
39 effects) and triggering of costly anti-predator responses (non-consumptive effects) (Lima and
40 Dill 1990, Cresswell 2008, Laundré et al. 2010). Non-consumptive effects of predation can be
41 major drivers of food web structure and dynamics (Cresswell 2008, Teckentrup et al. 2018).

42 Prey respond to predation risk with various risk management strategies at broad, intermediate
43 and fine spatial and temporal scales (Lima and Dill 1990, Guiden et al. 2019). At broad scales
44 (kilometers, days), predation risk associated to different areas may influence prey's choice of
45 home range, such as the breeding home range of migrant birds (Lima 2009, Morosinotto et al.

46 2010). At intermediate scales (hectares, hours), variation in predation risk within the home range
47 of a prey may affect its space use. For example, many bird species maximise their reproduction
48 by nesting where predation risk is the lowest, either where the regional abundance of main
49 predators is low (Forstmeier and Weiss 2004) or in habitats providing refuge against predation
50 (Anderson et al. 2015). Such refuges can offer complete or partial protection. At fine scales
51 (meters, minutes), when predator encounter is imminent, prey use anti-predator behavior such as
52 escape behavior (Ydenberg and Dill 1986). In many species, parents (such as incubating birds)
53 also provide offspring defense (Montgomerie and Weatherhead 1988, Lima 2009).

54 Prey risk management strategies also depend on predator and prey encounter rates (Gaynor et al.
55 2019). Indeed, space use patterns of predators and their primary prey (which are often the most
56 abundant and profitable prey, Stephens and Krebs 1986) tend to correlate (Fortin et al. 2005,
57 Arias-Del Razo et al. 2012). Thus, primary prey species can hardly avoid predation risk by
58 shifting their home ranges because predators actively search for them. Prey can rather adopt fine
59 scale risk management strategies such as defense behaviors or increased vigilance when using
60 risky areas (Laundré et al. 2001). On the other hand, incidental prey species, which are
61 consumed when encountered but are not actively searched, may manage risk of predation by
62 avoiding areas highly used by predators (Forstmeier and Weiss 2004, Avgar et al. 2015).

63 The landscape of fear concept offers a useful framework to understand how predation risk affects
64 prey behavior (Laundré et al. 2010, Gaynor et al. 2019). Laundré et al. (2010) defined the
65 landscape of fear as the spatial variation in prey perception of predation risk. Gaynor et al.
66 (2019) then framed the landscape of fear as part of a series of interdependent landscapes. First,
67 the physical landscape represents habitat features that interact with the biology (hunting mode,
68 body size, etc.) of predators and prey to determine their distributions and interactions. These

69 interactions then modulate the predation risk landscape and, accordingly, the landscape of fear.

70 Finally, the landscape of fear determines the responses of prey to predation risk, which
71 ultimately shape spatiotemporal variations in prey distribution and anti-predator behavior. Many
72 studies have used proxies of predation risk, such as habitat features (Dupuch et al. 2014), or
73 proxies of perceived predation risk, such as prey behavior (Willems and Hill 2009). Proxies are
74 useful but they can also lead to circular reasoning (Gaynor et al. 2019).

75 In active hunting predators, space use of active individuals, which can be measured at a fine
76 scale through GPS tracking, should closely approximate the landscape of predation risk since
77 they continuously prowl in search of prey (Schmitz et al. 2004). Some landscape of fear studies
78 measured predator movements to explain prey behavior while considering local density or space
79 use of predators, but with only a limited number of locations (Thaker et al. 2011, Kohl et al.
80 2018). For very active predators, a detailed assessment of movements is required to infer the
81 predation risk landscape (Poulin et al. 2020). Fortunately, improved data acquisition (Wilmers et
82 al. 2015) and modelling techniques (e.g., hidden Markov models, Patterson et al. 2017) now
83 allow to assess the behavior and active periods of predators from their fine scale movements.
84 However, the validity of using fine scale predator space use patterns as a surrogate to the
85 predation risk landscape should be demonstrated rather than assumed.

86 To better understand the effects of the landscape of fear on natural communities, we need to
87 simultaneously evaluate how predators generate the distribution of predation risk and how prey
88 respond to this distribution, ideally including all important predators and prey of the system
89 (Gaynor et al. 2019). Arctic terrestrial food webs are good models to study vertebrate predator-
90 prey interactions because they are relatively simple. One example is the tundra community of
91 Bylot Island (Nunavut, Canada), where the arctic fox (*Vulpes lagopus*) is the main terrestrial

92 predator. This canid is an active hunting predator that travels extensive daily distances within its
93 territory (Poulin et al. 2020). On Bylot, it feeds primarily on lemmings (*Lemmus trimucronatus*
94 and *Dicrostonyx groenlandicus*) which show important annual density fluctuations (Gruyer et al.
95 2008). During summer, foxes also collect eggs of the colonial nesting greater snow goose (*Anser*
96 *caerulescens atlanticus*) for immediate consumption and for storage (Bêty et al. 2001). As such,
97 foxes select in summer productive lemming habitats and patches of high snow goose nest density
98 (Grenier-Potvin et al. 2020). Because snow geese cannot avoid areas highly used by foxes, they
99 actively defend their nests when closely approached by a fox (Bêty et al. 2002). This defense
100 strategy is effective as long as geese remain close to their nest during incubation (Reed et al.
101 1995). Foxes also opportunistically prey upon nests of other ground nesting birds and are their
102 main nest predator (McKinnon and Bêty 2009, Gauthier et al. 2011). These incidental prey
103 mainly nest in mesic tundra, but some nest in micro-habitats that constrain fox movements and
104 thus offer protection (Lecomte et al. 2008). For example, islets of just a few spare meters located
105 in ponds may serve as refuges (Gauthier et al. 2015).

106 We assessed the effects of the predation risk landscape in the tundra community of Bylot Island.
107 We first defined and assessed empirically the *predator activity landscape*, that is the utilization
108 distribution of active foxes, using high frequency GPS data coupled with hidden Markov models.
109 We then experimentally tested if this predator activity landscape predicted (P1) the probability of
110 consumption of artificial prey, thus reflecting the predation risk landscape. Then, we investigated
111 the effect of the fox activity landscape on risk management strategy and nest distribution of the
112 bird community. We assessed the nest defense behavior of a primary prey (snow geese),
113 predicting (P2) that nest defense would be stronger in areas most used by foxes, where predation
114 risk is higher. We also assessed the effect of the predator activity landscape on the nest

115 distribution of incidental prey (P3), composed of bird species from different guilds. For species
116 nesting in common habitats easily accessed by foxes, we predicted (P3a) that the probability of
117 nest occurrence should be lowest in areas most used by foxes. Given the limited spatial
118 resolution of the fox activity landscape, we predicted that for species nesting in small refuges
119 such as islets, the probability of nest occurrence should be independent of the fox activity
120 landscape (P3b), as the location of refuges used for nesting should be independent of the
121 predation risk in the surrounding landscape.

122 **Methods**

123 *Study system*

124 We worked during summer 2019 in the southwest plain of Bylot Island (72°53' N, 79°54' W), in
125 Sirmilik National Park of Canada, Nunavut (Appendix S1: Fig. S1). The ecosystem is
126 characterized primarily by mesic tundra and polygonal wetlands (Grenier-Potvin et al. 2020). In
127 this system, arctic fox pairs have virtually no predators and are territorial. All studied individuals
128 had their territory in a snow goose colony composed of > 20,000 nesting pairs distributed over
129 70 km² (Béty et al. 2001, Béty et al. 2002). Lemming density was high enough to allow
130 reproduction of 5 of the 6 monitored fox pairs.

131 *Fox captures and movement tracking*

132 During May and June 2019, 13 foxes were captured using Softcatch #1 padded leghold traps
133 (Oneida Victor Inc. Ltd., Cleveland, OH, USA). These foxes represented 6 neighboring
134 territorial pairs and one additional individual, whose small home range overlapped two territories
135 (Fig. 1). Each fox was marked with colored ear tags allowing identification at a distance, and
136 was fitted with a GPS collar (95 g, 2.6–3.3% of body mass; Radio Tag-14, Milsar, Poland)

137 equipped with rechargeable batteries, a solar panel, and UHF transmission allowing remote data
138 download. We used a GPS fix interval of 4 min and average GPS location error was 11 m
139 (Poulin et al. 2020). The 6 fox territories represent our study area. The general contour of the
140 study area was drawn using the concave hull of fox GPS data (QGIS version 3.8.3, QGIS
141 Development Team 2019), excluding a few extra-territorial trips (Fig. 1). For each individual, we
142 used locations from 10 days at the end of June. Datasets were synchronized (\pm 2 days depending
143 on capture day and the timing of missing data; the 2 days following capture were excluded) and
144 matched laying and incubation of birds. Daily observations and automated cameras at fox dens
145 confirmed that we tracked all foxes foraging in the study area.
146 Capture techniques and immobilization procedures were approved by the UQAR Animal Care
147 Committee (CPA-64-16-169 R3) and field research was approved by the Joint Park Management
148 Committee of Sirmilik National Park of Canada (SIR-2018-28021).

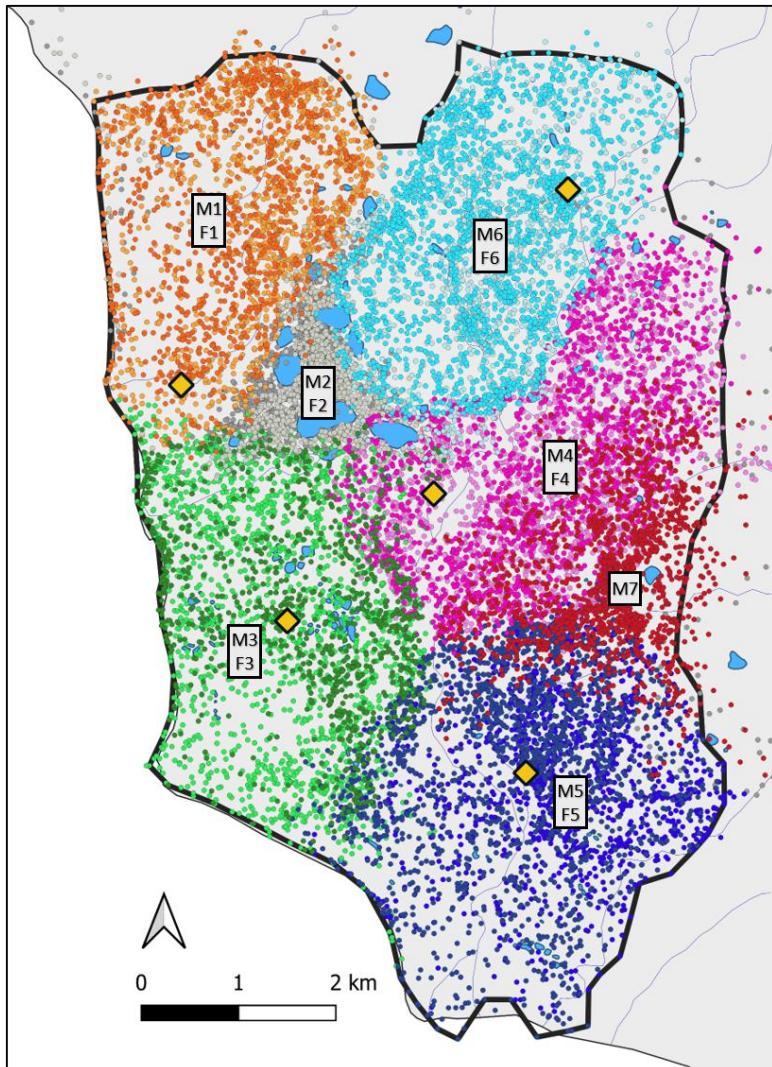


Fig. 1. Study area on Bylot Island (Nunavut, Canada) featuring GPS locations of 13 arctic foxes tracked during 10 days at the end of June 2019. Foxes occupied 6 territories (M7 had a small home range overlapping two territories) and pair members have related colors, as detailed in Appendix S1: Table S1. GPS locations were collected at 4-min fix intervals and the 20,961 data points shown are those classified in the active state by a hidden Markov model. Yellow diamonds locate the 5 reproductive dens (M2, F2 and M7 did not reproduce). The thick black line is the contour of the study area. Lakes and large ponds are in blue. See Appendix S1: Fig. S1 for the geographical context of the study area.

149 *Artificial prey experiment*

150 We conducted an artificial prey experiment using 8-g pieces of dried beef liver (measuring ca.

151 0.5 x 2 x 2 cm; Benny Bullys Sales Inc., ON, Canada; hereafter, baits) to assess predation risk.

152 On 4 July, we placed in each of the 6 fox territories 6–8 lines of ca. 10 baits each (total of 428

153 baits distributed in 44 curved lines each measuring 293 ± 77 m (mean \pm SD), see baits locations
154 in Appendix S1: Fig. S2A). Each bait line was located in a homogeneous habitat patch and bait
155 lines were distributed equally between wetland polygons and mesic tundra patches, at least 300
156 m from the study area limits to avoid potential border effects. Distance between adjacent baits
157 within bait lines was of 79 ± 7 m and distance between adjacent lines was 297 ± 118 m. Baits
158 were covered with moss or lichen to exclude predation by avian predators (as done for artificial
159 nests, Léandri-Breton and Béty 2020) and were visited after 4 days to assess their removal by
160 foxes. A piece of orange flag placed under each bait became visible when a bait had been
161 removed, thus facilitating assessment of predation events. After the experiment, camera traps
162 were placed during 5 ± 2 days at 6 locations (in 3 fox territories) to monitor the fate of baits,
163 which were replaced if consumed. Thirteen baits were taken, always by foxes, thus confirming
164 this species as the only bait consumer.

165 *Snow goose nest defense behavior*

166 The threat posed by predators is often much higher for young than for adults (Rosenbaum 2018).
167 Adults from species with large body size are almost immune to predation and therefore defend
168 their offspring rather than flee (Rosenbaum 2018). Flushing distance from an approaching
169 human is often used to assess a prey anti-predator strategy (Blumstein 2003) and represents a
170 good proxy for nest defence intensity. On Bylot, foxes essentially pose a threat to snow goose
171 eggs and chicks (Béty et al. 2001), so we measured the flushing distances of 458 incubating
172 females as an indicator of their level of nest defense (see nest locations in Appendix S1: Fig.
173 S2B). A small flushing distance (the observer is close to the nest when the female leaves)
174 indicates a high level of nest defense (Clermont et al. 2019). An observer approached a focal nest
175 by walking silently at a slow and constant pace, in a straight line, and measured flushing distance

176 with a telemeter or handheld GPS. To limit potential effects of incubation stage on goose nest
177 defense (Clermont et al. 2019), we performed 85% of flushing distance measures within 5 days
178 from June 14 to June 18 (we did remaining measures in the following days), which corresponds
179 to the first half of the incubation period. We also assessed clutch size which generally influences
180 nest defense intensity (Montgomerie and Weatherhead 1988), and we measured the starting
181 distance of the approach which affects flushing distance (Blumstein 2003). Focal nests were
182 located at least 300 m from the study area limits to avoid potential border effects.

183 *Nest distribution of incidental prey*

184 During the incubation period, we conducted thorough searches of bird nests other than snow
185 geese (i.e., incidental prey). In June, we walked repeatedly throughout the study area to detect
186 signs of reproductive birds (calling, distraction displays, bird flushing at close distance). This
187 was done through transect surveys conducted in mesic tundra, and intensive nest searches
188 performed in wetland patches, stony riverbanks and slopes, which are all easily accessible to
189 foxes. We also inspected enclaves, mostly islets in ponds, with a few peninsulas located in
190 complex wetlands, where nests are less accessible to foxes as they are surrounded by water. We
191 georeferenced 377 islets in the study area (Appendix S1: Fig. S3).

192 We found 109 nests from 13 species in the study area (see nest locations in Appendix S1: Fig.
193 S2C). A total of 44 nests from 10 species were located in areas easily accessible to foxes:
194 common-ringed plover (*Charadrius hiaticula*, n = 3), american golden plover (*Pluvialis*
195 *dominica*, n = 9), white-rumped sandpiper (*Calidris fuscicollis*, n = 2), arctic tern (*Sterna*
196 *paradisaea*, n = 2), rough-legged hawk (*Buteo lagopus*, n = 1), lapland longspur (*Calcarius*
197 *lapponicus*, n = 16), parasitic jaeger (*Stercorarius parasiticus*, n = 1), long-tailed jaeger
198 (*Stercorarius longicaudus*, n = 6), long-tailed duck (*Clangula hyemalis*, n = 1) and king eider

199 (Somateria spectabilis, n = 3). A total of 65 nests from 3 species were located in refuges:
200 cackling goose (*Branta hutchinsii*, n = 38), glaucous gull (*Larus hyperboreus*, n = 11) and red-
201 throated loon (*Gavia stellata*, n = 16).

202 *Predator activity landscape*

203 We defined the predator activity landscape as the utilization distribution (see below) of all foxes
204 in the active state within the study area. For opportunist active hunting predators like arctic
205 foxes, all travelling phases can be associated with hunting, therefore we used a hidden Markov
206 model (HMM) to assign GPS locations to an active or resting state (R package moveHMM,
207 Michelot et al. 2016). HMM decomposes GPS tracks into sequences associated to different
208 behavioral states, which differ from one another in their step lengths and turning angles
209 (Langrock et al. 2012). The active state is characterized by long step lengths and small turning
210 angles, and the resting state with short step lengths and large turning angles. The HMM included
211 time of the day as a covariate to reflect the circadian rhythm of foxes (Grenier-Potvin et al.
212 2020). Models using a Weibull distribution for step lengths and a wrapped Cauchy distribution
213 for turning angles yielded the most parsimonious model (HMM construction and model selection
214 is detailed in Grenier-Potvin et al. 2020).

215 Then, we used Kernel Density Estimation (QGIS Heatmap plugin) to map the fox utilization
216 distribution (UD) using only active locations. UDs quantify the intensity of space use (from low
217 to high probability density of GPS locations) by tracked animals and thus identify areas where
218 animals are most likely to be found (Fortin et al. 2005, Thaker et al. 2011). We used 10-m² pixels
219 to map UD scores, and a fixed UD smoothing parameter (called radius in QGIS, which is
220 equivalent to the kernel bandwidth) to specify the distance at which GPS locations influence UD
221 scores. As the choice of the UD smoothing parameter can affect prediction tests, we performed a

222 sensitivity analysis. We ran statistical models (presented in the following section) for 5 UD
223 smoothing parameters ranging from 200 to 400 m (50-m increments). As foxes in their active
224 state traveled 232 ± 145 m (mean \pm SD, see Results) between GPS fixes obtained at 4-min
225 intervals, the chosen range of smoothing parameters yielded fine resolution activity landscapes
226 that reflected the scale of our data. Using smaller parameter values would have underestimated
227 the use of areas located between GPS locations, whereas using larger parameter values would
228 have overestimated the use of areas located on each side of the fox track. UD scores were
229 standardized from 0 to 1 in each of the 5 UDs.

230 *Statistical models*

231 We tested the effect of the fox activity landscape on the probability of predation of baits (P1),
232 snow goose nest defense behavior (P2) and the nest distribution of fox incidental prey (P3). A
233 first step consisted in extracting the fox UD score at all locations used in the models, that is
234 locations of baits, nests of tested snow geese, and nests and available nesting locations of
235 incidental birds (see below).

236 1) Probability of predation of baits

237 We used a generalized linear mixed model (R package lme4, Bates et al. 2015) with a logit-link
238 function and a binomial distribution to test the effect of fox UD score on the probability of
239 predation of baits (0 = not predated, 1 = predated), with the ID of the bait line nested in the ID of
240 the fox territory as random effects. We fitted one model for each of the 5 UDs defined with
241 different smoothing parameters.

242 2) Snow goose nest defense behavior

243 We used a linear mixed model to test the effect of fox UD score on goose flushing distance.
244 Goose flushing distance was square-root transformed to respect the assumption of normality and
245 homoscedasticity in models' residuals. The other fixed effects included in the models were clutch
246 size, starting distance of the approach, and date of observation. All covariates were centered and
247 standardized to facilitate interpretation of model estimates (Schielzeth 2010). We included as
248 random effects the ID of the fox territory and the ID of the observer performing the approach.
249 We fitted one model for each of the 5 UDs.

250 3) Nest distribution of incidental prey

251 We used conditional logistic regressions with a use-available design (function clogit in R
252 package survival, Therneau et al. 2020) to test the effect of fox UD score on the distribution of
253 bird nests of fox incidental prey species. We analyzed separately species nesting in habitats
254 easily accessible to foxes (first set of models, P3a) and species nesting in refuges (second set of
255 models, P3b).

256 In the first set of models, we compared fox UD scores at bird nests (used locations) to fox UD
257 scores at random sites (available locations). We considered as available locations potential
258 nesting sites located in the study area, excluding water bodies. Each bird nest location was paired
259 to 50 random locations drawn from an area surrounding the nest (hereafter, the *nest area*). As
260 tundra nesting birds have various natural histories, including nesting habitat and social system,
261 they likely select nesting sites at different spatial scales which are unknown. Hence, we could not
262 justify *a priori* a single radius for the nest area. We therefore repeated analyses after forcing
263 random locations within 5 radii varying from 1000 m to 3000 m (increments of 500 m), thus
264 fitting 25 models (5 UDs x 5 nest area radii).

265 In the second set of models, we again compared fox UD scores at bird nests (used locations) to
266 fox UD scores at available sites. However, we used as available locations potential nesting sites
267 located in the study area and surrounded by water, drawing from our 377 georeferenced islets.
268 Each bird nest location was paired to 50 islets chosen randomly from the area surrounding the
269 nest. Less than 50 islets were sometimes available, so we assessed whether this affected results
270 (Appendix S2). Since fox UD scores are smoothed values obtained from GPS locations collected
271 at a 4-min fix interval, they reflect fox utilization of the surrounding area rather than micro-
272 habitat use, and the UD score of an islet could be > 0 even if no fox visited the islet. As for the
273 first set of models, we fitted 25 models (5 UD x 5 nest area radii).

274 All analyses were conducted in R (version 3.6.1, R Development Core Team 2019). We
275 validated the assumptions of normality, homoscedasticity, non-collinearity among fixed effects,
276 and independence of residuals for all models. Values are expressed as mean \pm SD.

277 **Results**

278 *Fox activity landscape*

279 A total of 45,140 fixes were acquired for 13 foxes tracked for 10 days (Fig. 1). The active
280 behavioral state was assigned to $46 \pm 9\%$ of locations per individual (range 31–60%, Appendix
281 S1: Table S1) for a total of 20,961 GPS locations. Average step length and turning angle were
282 232 ± 145 m and 55° for active locations, and 9 ± 9 m and 116° for resting locations (see
283 Grenier-Potvin et al. 2020 for detailed HMM results). The representation of the fox activity
284 landscape (Fig. 2, UD smoothing parameter = 300 m) shows obvious heterogeneity in the
285 intensity of space use by foxes. This heterogeneity decreased, but overall patterns remained as
286 smoothing parameters varied from 200 m to 400 m (Fig. 2, Appendix S1: Fig. S4). The predator
287 activity landscape identified areas intensively used by some foxes, such as the small central

288 territory where individuals M2 and F2 lived in a restricted area, and sections M7 shared with M4,
289 F4, M5 and F5 (Figs. 1, 2).

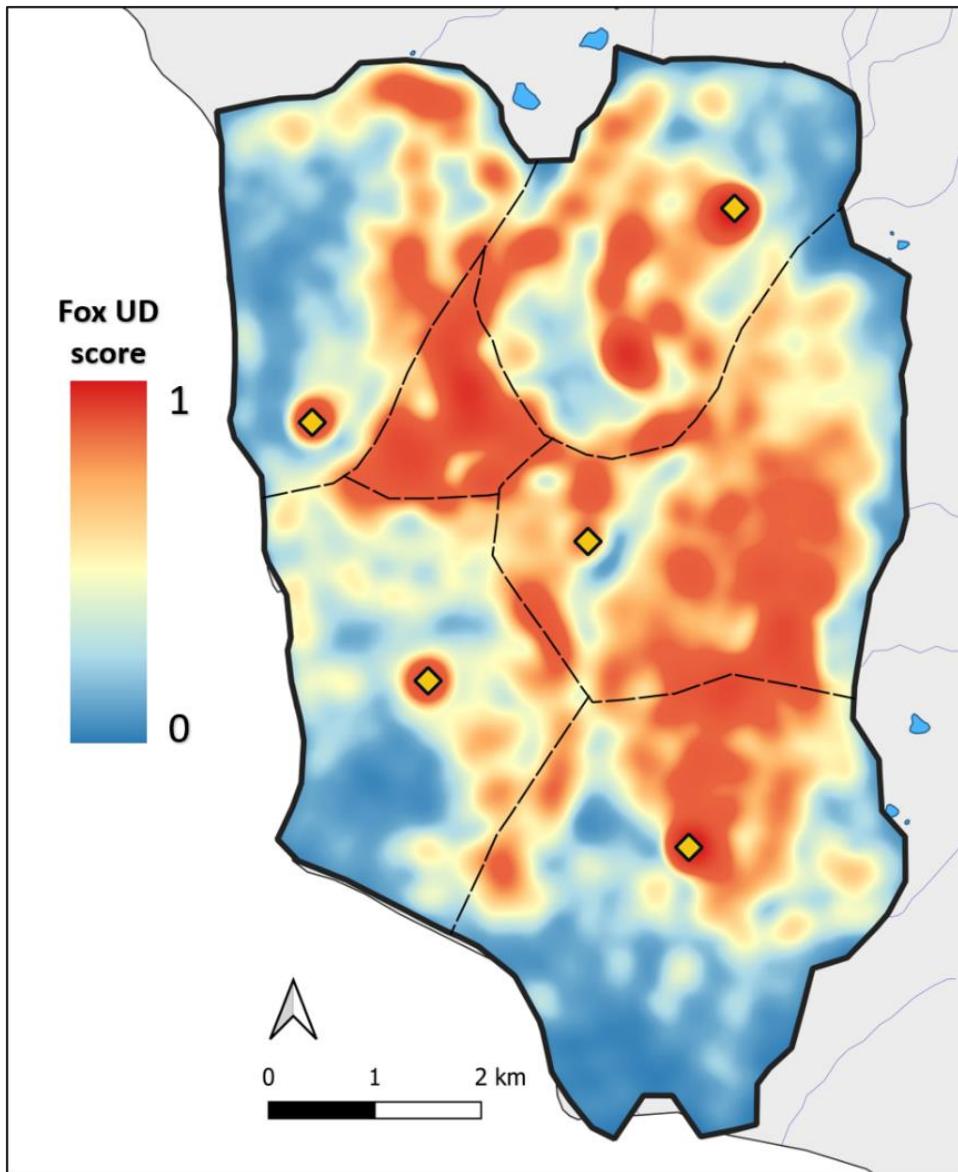


Fig. 2. Arctic fox activity landscape generated from 20,961 GPS locations classified in the active state by a hidden Markov model. The activity landscape reflects fox utilization distribution (UD) based on data from 13 individuals living in 6 territories, tracked during 10 days at the end of June 2019 on Bylot Island. A UD smoothing parameter of 300 m was used to generate this activity landscape (see Appendix S1: Fig. S4 for activity landscapes generated from other smoothing parameters). The color scale reflects fox UD score (from 0 to 1) and thus probability of presence of a fox. Yellow diamonds locate the 5 reproductive dens, dotted lines identify the approximate boundaries of fox pair territories, and the thick black line is the contour of the study area.

290 *Probability of predation of baits*

291 The artificial prey experiment showed high adequacy between the predator activity landscape
292 and the predation risk landscape. Baits were more likely to be consumed where fox UD score
293 was high (Table 1, Fig. 3a), whatever the UD smoothing parameter (Table 1).

Table 1. Results from binomial mixed models testing the effect of fox UD score on the probability of predation of baits, with patch ID nested in territory ID fitted as random effects, for the 5 UD s with smoothing parameter ranging from 200 to 400 m (n = 428 baits).

UD smoothing parameter (m)	Fixed effect	Estimate [95% CI]	z value	p value
200	(Intercept)	-0.25 [-1.17, 0.68]	-0.60	0.546
	Fox UD score	3.56 [-0.02, 7.45]	1.91	0.056
250	(Intercept)	-0.35 [-1.29, 0.60]	-0.82	0.414
	Fox UD score	3.28 [0.31, 6.49]	2.12	0.034
300	(Intercept)	-0.48 [-1.44, 0.49]	-1.07	0.284
	Fox UD score	3.24 [0.59, 6.09]	2.36	0.013
350	(Intercept)	-0.61 [-1.61, 0.38]	-1.31	0.191
	Fox UD score	3.23 [0.79, 5.84]	2.56	0.011
400	(Intercept)	-0.73 [-1.77, 0.29]	-1.50	0.133
	Fox UD score	3.18 [0.89, 5.62]	2.69	0.007

See Appendix S1: Table S2 for variance values of random effects.

294 *Snow goose nest defense behavior*

295 Snow geese showed higher level of nest defense when nesting in areas of high predation risk, as
296 shown by the negative relationship between flushing distance and fox UD score (Table 2, Fig.
297 3b). Although slope estimates were consistently negative for the 5 UD s, the slope lessened and
298 lost its significance as the UD smoothing parameter increased. Geese also showed a weaker level
299 of nest defense when they had a relatively small clutch and saw the observer approaching from
300 far away, as shown by the significant effects of clutch size and starting distance on flushing
301 distance (no effect of smoothing parameter, Table 2). Flushing distance did not vary with
302 observation date.

Table 2. Results from linear mixed models testing the effect of fox UD score on goose flushing distance. Number of eggs, starting distance of the observer and date were included as covariates. Territory ID and observer ID were fitted as random effects and models were repeated for the 5 UDs with smoothing parameter ranging from 200 to 400 m (n = 458 goose nests). All fixed effects are standardized and the effect of interest (fox UD score) is highlighted in gray. Significant effects are in bold.

UD smoothing parameter (m)	Fixed effect	Estimate [95% CI]	df	t value	p value
200	(Intercept)	7.34 [5.98, 8.74]	2.79	11.7	0.002
	Fox UD score	-0.26 [-0.47, -0.04]	417.61	-2.36	0.019
	Number of eggs	-0.30 [-0.48, -0.11]	424.33	-3.15	0.002
	Starting distance	1.46 [1.25, 1.67]	265.55	13.72	< 0.001
250	Date	-0.17 [-0.46, 0.10]	42.69	-1.29	0.203
	(Intercept)	7.34 [5.98, 8.74]	2.79	11.71	0.002
	Fox UD score	-0.25 [-0.47, -0.03]	410.57	-2.25	0.025
	Number of eggs	-0.3 [-0.49, -0.11]	424.34	-3.15	0.002
300	Starting distance	1.45 [1.25, 1.67]	264.14	13.7	<0.001
	Date	-0.17 [-0.45, 0.11]	42.14	-1.27	0.211
	(Intercept)	7.33 [5.99, 8.71]	2.78	11.87	0.002
	Fox UD score	-0.23 [-0.45, 0.01]	402.52	-1.98	0.049
350	Number of eggs	-0.3 [-0.49, -0.11]	424.37	-3.15	0.002
	Starting distance	1.46 [1.25, 1.67]	264.68	13.69	<0.001
	Date	-0.16 [-0.45, 0.11]	42.35	-1.21	0.230
	(Intercept)	7.33 [6.01, 8.68]	2.78	12.08	0.002
400	Fox UD score	-0.20 [-0.42, 0.04]	396.55	-1.69	0.091
	Number of eggs	-0.30 [-0.48, -0.11]	424.42	-3.13	0.002
	Starting distance	1.46 [1.25, 1.67]	266.50	13.67	<0.001
	Date	-0.16 [-0.44, 0.12]	43.01	-1.17	0.250

See Appendix S1: Table S3 for variance values of random effects.

303 *Nest distribution of incidental prey*
 304 For bird species nesting in habitats easily accessible to foxes, nests were more likely to occur
 305 where fox UD score was low, compared to random locations (Table 3, Fig. 3c). Specifically, the
 306 probability of nest occurrence was approximately twice higher than the probability of occurrence

307 of a random location where fox UD score was the lowest, and the probability of nest occurrence
308 also declined steeply as fox presence increased (Fig. 3c). The effect of fox UD score on nest
309 distribution was significant or almost significant (with p values only slightly over 0.05 and the
310 upper limit of confidence intervals slightly over 0) for all 5 fox activity landscapes (smoothing
311 parameters of 200–400 m) and 5 nest area sizes (radii of 1000–3000 m) (Table 3).

312 For bird species nesting in refuges, fox UD score did not affect the probability of nest
313 occurrence, whatever the smoothing parameter or nest area radius (Table 3). Fox UD scores of
314 nesting locations were not statistically different from those of random islets (Table 3). Variation
315 in the number of random islets available for testing did not affect results (Appendix S2).

316

Table 3. Results from conditional logistic regressions with a use-available design testing the effect of fox UD score on the nest distribution of (1) birds nesting in habitats easily accessible to foxes (n = 44 nests from 10 species) and (2) birds nesting in micro-habitats providing a refuge against foxes (n = 65 nests from 3 species). The fox UD score of each nest located in an easily accessible habitat was compared to the fox UD scores of 50 random locations surrounding the nest within a predetermined nest area. The fox UD score of each nest located in a refuge was compared to the fox UD score of ≤ 50 islets surrounding the nest within the nest area. Coefficient estimates are presented for 25 models, each reflecting a given size of the nest area (from 1000 to 3000 m) and UD smoothing parameter (from 200 to 400 m). Significant effects are in bold.

Radius of nest area (m)	UD smoothing parameter (m)	(1) Nests in easily accessible habitats			(2) Nests in refuges		
		Coefficient [95% CI]	z value	p value	Coefficient [95% CI]	z value	p value
1000	200	-9.81 [-18.42, -1.20]	-2.23	0.026	0.93 [-7.36, 9.23]	0.22	0.826
	250	-7.12 [-13.86, -0.39]	-2.07	0.038	0.50 [-6.14, 7.13]	0.15	0.884
	300	-5.58 [-11.17, -0.002]	-1.96	0.050	1.13 [-5.45, 5.70]	0.04	0.965
	350	-4.46 [-9.23, 0.32]	-1.83	0.067	-0.20 [-5.06, 4.67]	-0.08	0.937
	400	-3.53 [-7.69, 0.63]	-1.66	0.097	-0.46 [-4.84, 3.92]	-0.20	0.838
1500	200	-10.61 [-18.60, -2.61]	-2.60	0.009	4.43 [-1.66, 10.52]	1.43	0.154
	250	-7.70 [-13.82, -1.57]	-2.46	0.014	3.24 [-1.47, 7.96]	1.35	0.178
	300	-6.04 [-11.05, -1.04]	-2.37	0.018	2.40 [-1.49, 6.30]	1.21	0.226
	350	-4.89 [-9.13, -0.66]	-2.26	0.024	1.79 [-1.54, 5.12]	1.05	0.293
	400	-4.01 [-7.68, -0.34]	-2.14	0.032	1.36 [-1.58, 4.31]	0.91	0.365
2000	200	-9.87 [-17.33, -2.41]	-2.59	0.009	3.50 [-1.79, 8.78]	1.30	0.195
	250	-7.04 [-12.67, -1.41]	-2.45	0.014	2.44 [-1.64, 6.51]	1.17	0.241
	300	-5.42 [-9.95, -0.88]	-2.34	0.019	1.74 [-1.63, 5.11]	1.01	0.312
	350	-4.29 [-8.07, -0.50]	-2.22	0.026	1.28 [-1.60, 4.16]	0.87	0.385
	400	-3.44 [-6.68, -0.21]	-2.09	0.037	0.97 [-1.56, 3.50]	0.75	0.453
2500	200	-8.05 [-14.82, -1.28]	-2.33	0.020	3.47 [-1.82, 8.76]	1.29	0.199
	250	-5.68 [-10.77, -0.59]	-2.19	0.029	2.55 [-1.51, 6.60]	1.23	0.218
	300	-4.35 [-8.44, -0.26]	-2.08	0.037	1.92 [-1.41, 5.25]	1.13	0.258
	350	-3.45 [-6.86, -0.04]	-1.98	0.048	1.47 [-1.38, 4.31]	1.01	0.312
	400	-2.78 [-5.69, 0.14]	-1.87	0.062	1.15 [-1.36, 3.64]	0.90	0.371
3000	200	-7.03 [-13.61, -0.45]	-2.10	0.036	3.78 [-1.48, 9.05]	1.41	0.159
	250	-4.99 [-9.90, -0.08]	-1.99	0.047	2.79 [-1.21, 6.80]	1.37	0.171
	300	-3.83 [-7.75, 0.09]	-1.91	0.056	2.16 [-1.11, 5.43]	1.30	0.195
	350	-3.02 [-6.28, 0.23]	-1.82	0.068	1.70 [-1.07, 4.48]	1.20	0.229
	400	-2.42 [-5.19, 0.35]	-1.71	0.087	1.37 [-1.06, 3.80]	1.11	0.269

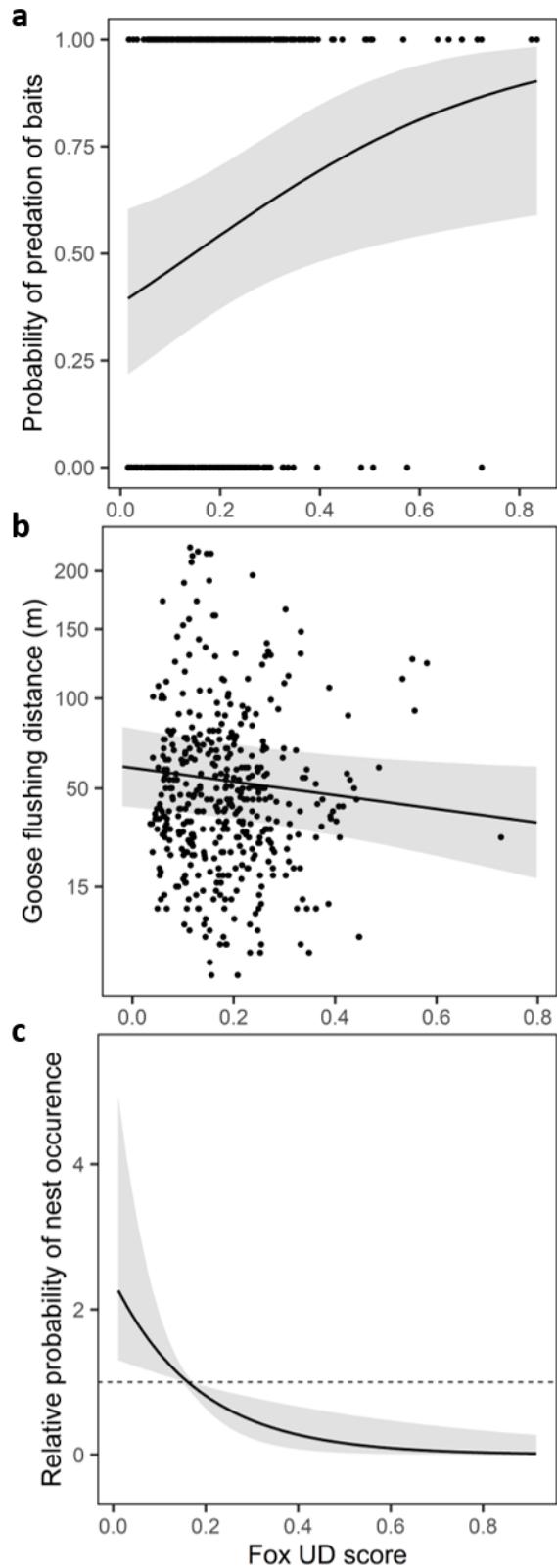


Fig. 3. Predicted effect of fox UD score on (a) probability of predation of baits (0 = bait not eaten, 1 = bait eaten, n = 428), (b) goose flushing distance (n = 458) and (c) relative probability of occurrence of nests from birds nesting in habitats easily accessible to foxes (n = 44 nests from 10 species). In (b), we back-transformed goose flushing distance and fox UD score before plotting (goose flushing distance had been square-root transformed and fox UD score had been centered and standardized in linear models), leading to irregular y-axis increments. In (c) the dashed horizontal line represents a relative probability of occurrence of 1, with values below and above 1 indicating lower and higher probabilities of occurrence than random, respectively. The gray area represents the 95% confidence interval of (a) the fitted logistic regression, (b) the linear regression and (c) the relative probability of occurrence obtained by bootstrap. For these representations we used fox UD scores generated with an intermediate smoothing parameter of 300 m, and (c) nest areas generated with an intermediate radius of 2000 m.

317 **Discussion**

318 Considering simultaneously all actors interacting in a heterogeneous landscape is needed to fully
319 assess the ecological context of the landscape of fear and its consequences on natural
320 communities (Gaynor et al. 2019). Using high resolution arctic fox GPS data, behavioral
321 observations and field experiments, we demonstrated that fine scale variation in space use of
322 active predators accurately reflects spatial variation in predation risk, and explains anti-predator
323 behavior of a main prey and nest distribution of some incidental prey species in an Arctic
324 terrestrial community (Fig. 4). Overall, our study demonstrates the impacts of predator activity
325 on the behavioral decisions and distribution of prey and highlights the spatial dimension of
326 predator-prey relationships.

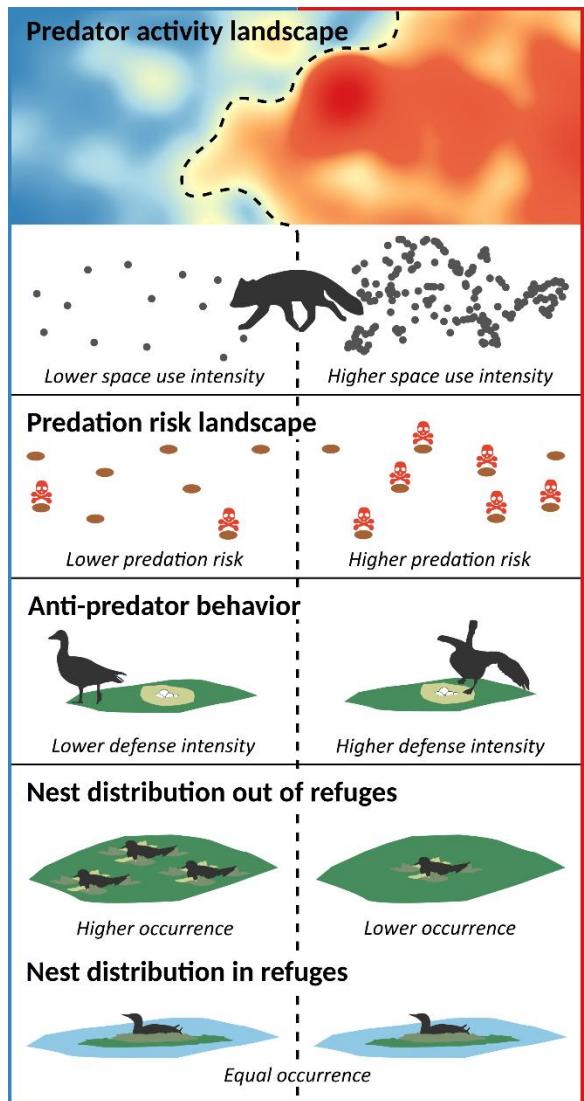


Fig. 4. Landscape of fear context in a terrestrial Arctic community. The predator activity landscape generates a landscape of predation risk and predicts anti-predator response and distribution of prey. The illustrated predator activity landscape shows the multiple spatial gradients of intensity in arctic fox space use (low in blue, high in red). Causation between the predator activity landscape and the predation risk landscape is demonstrated by an artificial prey experiment. The predator activity landscape predicts anti-predator behavior of a main prey (here, snow goose) and nest distribution of incidental prey (here, a shorebird) nesting in habitats accessible to foxes. However, the nest distribution of incidental prey nesting in predation refuges such as islets (here, a loon) is independent of the predator activity landscape at its measured spatial resolution.

327 *The predator activity landscape as a predation risk landscape*

328 The use of fox movement data collected at a high frequency, in combination with the
329 identification of active and resting behavioral states yielded a predator activity landscape that
330 robustly depicted fine scale variation in fox intensity of space use in our study area. An artificial
331 prey experiment using baits demonstrated that the probability of predation was higher in areas
332 highly used by foxes, and therefore that spatial variation in fox space use was related to
333 predation risk for prey. Our sensitivity analyses also confirmed the robustness of our results,
334 which were consistent across our range of UD smoothing parameters (Tables 1, 2, 3). Most
335 importantly, when the adequacy between the predator activity landscape and the predation risk
336 landscape is demonstrated, the predator activity landscape allows to identify predator “hotspots”
337 where risk of predation should be the highest, and thus creates opportunities to better understand
338 the spatial dimension of predator-prey interactions.

339 Furthermore, to obtain a good estimation of the probability of predator-prey encounter and thus
340 predation risk, it is crucial to accurately model spatial variation in predator space use intensity
341 (or predator density), which is not always possible using proxies of predator space use (e.g.,
342 habitat features), or when only a limited number of predator locations are used. Also, prey in
343 multi-predator systems may have to deal with multiple and contrasting landscapes of risk
344 (Thaker et al. 2011, Gaynor et al. 2019). In our system, even though foxes are the main predators
345 of all nesting prey (Gauthier et al. 2011), the occasional presence of territorial ermines (*Mustela*
346 *erminea*) in years of high lemming abundance may increase predation risk in some areas, while
347 nesting association with snowy owls may reduce predation risk (Bêty et al. 2001). Our predator
348 activity landscape accurately depicted spatial variation in predation risk as we were able to collar
349 all foxes living in our study area, where neither ermines nor snowy owls were detected.

350 *Goose nest defense intensity partly explained by the predator activity landscape*

351 It is difficult for primary prey species to reduce their exposure to predation risk because they are
352 actively searched by predators. As such, highly conspicuous nesting snow geese can hardly use
353 spatial avoidance to reduce predation risk as active foxes select patches where goose nest density
354 is highest (Grenier-Potvin et al. 2020). Geese can nonetheless adopt a fine scale response by
355 using nest defense when predation risk of their nest is imminent (Bêty et al. 2002, Lima 2009).
356 We indeed found that snow geese nesting in areas highly used by foxes showed a higher level of
357 nest defense compared to geese nesting in less used areas. This likely results from plastic
358 adjustments of anti-predator behavior in response to variation in predation risk, such as female
359 ungulates showing greater levels of vigilance when foraging in habitats associated to higher
360 predation risk caused by wolf presence (Laundré et al. 2001). Assessing anti-predator behavior
361 on the same individuals along a gradient of predation risk (Fontaine and Martin 2006, Mathot et
362 al. 2011) would be required to fully understand the underlying mechanisms explaining the
363 relationship between snow geese nest defence and the predator activity landscape. Nonetheless,
364 our results suggest that predator space use impacts large prey behavior, which ultimately imposes
365 costs on their fitness (Cresswell 2008).

366 The effect of the fox activity landscape on goose flushing distances was moderate, and model
367 outputs slightly differed according to UD smoothing parameters (Table 2). Variables affecting
368 goose nest defense other than those considered in this study, like the parent's physiological state
369 or the presence of conspecifics (Kazama et al. 2011), may further explain variation in goose nest
370 defense. Also, although we limited effects of the incubation stage of nest defense intensity by
371 approaching nests during a short period of time and by controlling potential effects of date in our
372 models, nesting asynchrony may have created uncontrolled variation in nest defense intensity.

373 Finally, aspects of the physical landscape that affect nest visibility and thus predator detection
374 may affect how prey perceive the level of predation risk and respond to the predator activity
375 landscape (Gaynor et al. 2019).

376 *Habitat structure modulates the effect of predator activity landscape on incidental prey*
377 As proposed by Gaynor et al (2019), we found evidence that the physical landscape can
378 intervene in the ecological context of the landscape of fear. Indeed, cackling geese, glaucous
379 gulls and red-throated loons nest on islets that are poorly accessible to foxes and serve as refuges
380 (Gauthier et al. 2015). Hence, species using such structures can better afford to have their nest
381 surrounded by a relatively risky landscape, explaining why they did not respond to the fox
382 activity landscape at its measured spatial resolution. This is not the case for species nesting in
383 adjacent habitats easily accessible to foxes. Indeed, the probability of occurrence of these other
384 nesting birds was lower in areas heavily used by foxes. These species may perceive predation
385 risk and avoid nesting in areas highly used by foxes, as birds can shift nest location when
386 encountering predators during nest building (Peluc et al. 2008). Selection of safe habitats may
387 also be fixed genetically through selection. For example, some shorebirds nest strictly on stony
388 riverbanks (Léandri-Breton and Béty 2020), a habitat avoided by foxes (Grenier-Potvin et al.
389 2020). How habitat structure modulates the predator activity landscape and its effects on
390 incidental prey is a rich topic for research on predator-mediated interactions between prey
391 species.

392 The relationship between the predator activity landscape and nest distribution may also result
393 from consumptive effects of predation, as nests located in areas highly used by foxes may have
394 been preyed upon before being detected by observers. Monitoring fine-scale bird movements
395 during nest establishment (Gilbert et al. 2016) and determining nest location prior to any nest

396 predation event should help differentiating the roles of consumptive and non-consumptive effects
397 of predation, and to investigate the ability of nesting birds to perceive and respond to predation
398 risk.

399 Finally, animals face a variety of physiological, phylogenetic or ecological constraints that limit
400 their ability to assess predation risk and respond to the landscape of fear (Jordan and Ryan 2015,
401 Gaynor et al. 2019). Measuring the landscape of fear directly, by assessing how prey perceive
402 predation risk, would increase our understanding of complex relationships between predation
403 risk and prey responses, despite the challenges that this approach entails (Gaynor et al. 2019).

404 *Conclusion*

405 Our study demonstrates the value of using fine scale predator movements to characterize the
406 landscape of predation risk in landscape of fear studies. It also highlights how the predator
407 activity landscape influences the anti-predator behavior of a main prey and the nest distribution
408 of incidental prey species from different guilds. Assessing the effects of the landscape of fear in
409 a community allows to better understand prey species distribution and behavior, providing
410 insights on the structure and functioning of a community.

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420 J. Clermont, J. Béty and D. Berteaux conceived the study with contribution from coauthors. All
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423 Clermont led the writing, with contribution from coauthors.

424 **Literature Cited**

425 Anderson, H. B., J. Madsen, E. Fuglei, G. H. Jensen, S. J. Woodin, and R. van der Wal. 2015.
426 The dilemma of where to nest: influence of spring snow cover, food proximity and predator
427 abundance on reproductive success of an arctic-breeding migratory herbivore is dependent on
428 nesting habitat choice. *Polar Biology* 38:153–162.

429 Arias-Del Razo, I., L. Hernández, J. W. Laundré, and L. Velasco-Vázquez. 2012. The landscape
430 of fear: habitat use by a predator (*Canis latrans*) and its main prey (*Lepus californicus* and
431 *Sylvilagus audubonii*). *Canadian Journal of Zoology* 90:683–693.

432 Avgar, T., J. A. Baker, G. S. Brown, J. S. Hagens, A. M. Kittle, E. E. Mallon, M. T. McGreer, A.
433 Mosser, S. G. Newmaster, B. R. Patterson, D. E. B. Reid, A. R. Rodgers, J. Shuter, G. M.
434 Street, I. Thompson, M. J. Turetsky, P. A. Wiebe, and J. M. Fryxell. 2015. Space-use
435 behaviour of woodland caribou based on a cognitive movement model. *Journal of Animal
436 Ecology* 84:1059–1070.

437 Bates, D., M. Mächler, B. M. Bolker, and S. C. Walker. 2015. Fitting linear mixed-effects
438 models using lme4. *Journal of Statistical Software* 67:1–48.

439 Béty, J., G. Gauthier, J.-F. Giroux, and E. Korpimäki. 2001. Are goose nesting success and
440 lemming cycles linked? Interplay between nest density and predators. *Oikos* 93:388–400.

441 Bêty, J., G. Gauthier, E. Korpimäki, and J.-F. Giroux. 2002. Shared predators and indirect
442 trophic interactions: lemming cycles and Arctic-nesting geese. *Journal of Animal Ecology*
443 71:88–98.

444 Blumstein, D. T. 2003. Flight-initiation distance in birds is dependent on intruder starting
445 distance. *The Journal of Wildlife Management* 67:852–857.

446 Clermont, J., D. Réale, M.-E. Lindsay, and J.-F. Giroux. 2019. Plasticity, state-dependency, and
447 individual consistency in Canada goose nest defense behavior. *Behavioral Ecology and*
448 *Sociobiology* 73:66.

449 Cresswell, W. 2008. Non-lethal effects of predation in birds. *Ibis* 150:3–17.

450 Dupuch, A., D. W. Morris, and W. D. Halliday. 2014. Patch use and vigilance by sympatric
451 lemmings in predator and competitor-driven landscapes of fear. *Behavioral Ecology and*
452 *Sociobiology* 68:299–308.

453 Fontaine, J. J., and T. E. Martin. 2006. Parent birds assess nest predation risk and adjust their
454 reproductive strategies. *Ecology Letters* 9:428–434.

455 Ford, A. T., J. R. Goheen, T. O. Otieno, L. Bidner, L. A. Isbell, T. M. Palmer, D. Ward, R.
456 Woodroffe, and R. M. Pringle. 2014. Large carnivores make savanna tree communities less
457 thorny. *Science* 346:346–349.

458 Forstmeier, W., and I. Weiss. 2004. Adaptive plasticity in nest-site selection in response to
459 changing predation risk. *Oikos* 104:487–499.

460 Fortin, D., H. L. Beyer, M. S. Boyce, D. W. Smith, T. Duchesne, and J. S. Mao. 2005. Wolves
461 influence elk movements: behavior shapes a trophic cascade in Yellowstone National Park.
462 *Ecology* 86:1320–1330.

463 Gauthier, G., D. Berteaux, J. Béty, A. Tarroux, J.-F. Therrien, L. McKinnon, P. Legagneux, and
464 M.-C. Cadieux. 2011. The tundra food Web of Bylot Island in a changing climate and the role
465 of exchanges between ecosystems. *Ecoscience* 18:223–235.

466 Gauthier, G., P. Legagneux, M.-A. Valiquette, M.-C. Cadieux, and J.-F. Therrien. 2015. Diet and
467 reproductive success of an Arctic generalist predator: interplay between variations in prey
468 abundance, nest site location, and intraguild predation. *The Auk* 132:735–747.

469 Gaynor, K. M., J. S. Brown, A. D. Middleton, M. E. Power, and J. S. Brashares. 2019.
470 Landscapes of fear: spatial patterns of risk perception and response. *Trends in Ecology &*
471 *Evolution* 34:355–368.

472 Gilbert, N. I., R. A. Correia, J. P. Silva, C. Pacheco, I. Catry, P. W. Atkinson, J. A. Gill, and A.
473 M. A. Franco. 2016. Are white storks addicted to junk food? Impacts of landfill use on the
474 movement and behaviour of resident white storks (*Ciconia ciconia*) from a partially migratory
475 population. *Movement Ecology* 4:7.

476 Grenier-Potvin, A., J. Clermont, G. Gauthier, and D. Berteaux. 2020. Prey and habitat
477 distribution are not enough to explain predator habitat selection: addressing intraspecific
478 interaction constraints, behavioural state and time. *Journal of Animal Ecology*, submitted.

479 Gruyer, N., G. Gauthier, and D. Berteaux. 2008. Cyclic dynamics of sympatric lemming
480 populations on Bylot Island, Nunavut, Canada. *Canadian Journal of Zoology* 86:910–917.

481 Guiden, P. W., S. L. Bartel, N. W. Byer, A. A. Shipley, and J. L. Orrock. 2019. Predator–prey
482 interactions in the Anthropocene: reconciling multiple aspects of novelty. *Trends in Ecology
483 & Evolution* 34:616–627.

484 Jordan, L. A., and M. J. Ryan. 2015. The sensory ecology of adaptive landscapes. *Biology
485 Letters* 11:20141054.

486 Kazama, K., Y. Niizuma, K. Q. Sakamoto, and Y. Watanuki. 2011. Factors affecting individual
487 variation in nest-defense intensity in colonially breeding black-tailed gulls (*Larus*
488 *crassirostris*). Canadian Journal of Zoology 89:938–944.

489 Kohl, M. T., D. R. Stahler, M. C. Metz, J. D. Forester, M. J. Kauffman, N. Varley, P. J. White,
490 D. W. Smith, and D. R. MacNulty. 2018. Diel predator activity drives a dynamic landscape of
491 fear. Ecological Monographs 88:638–652.

492 Langrock, R., R. King, J. Matthiopoulos, L. Thomas, D. Fortin, and J. M. Morales. 2012.
493 Flexible and practical modeling of animal telemetry data: hidden Markov models and
494 extensions. Ecology 93:2336–2342.

495 Laundré, J. W., L. Hernández, and K. B. Altendorf. 2001. Wolves, elk, and bison: reestablishing
496 the “landscape of fear” in Yellowstone National Park. U.S.A. Canadian Journal of Zoology
497 79:1401–1409.

498 Laundré, J. W., L. Hernández, and W. J. Ripple. 2010. The landscape of fear: ecological
499 implications of being afraid. The Open Ecology Journal 3:1–7.

500 Léandri-Breton, D.-J., and J. Béty. Vulnerability to predation may affect species distribution:
501 plovers with broader Arctic breeding range nest in safer habitat. Scientific Reports 10:5032.

502 Lima, S. L. 2009. Predators and the breeding bird: behavioral and reproductive flexibility under
503 the risk of predation. Biological Reviews 84:485–513.

504 Lima, S. L., and L. M. Dill. 1990. Behavioral decisions made under the risk of predation: a
505 review and prospectus. Canadian Journal of Zoology 68:619–640.

506 Mathot, K. J., P. J. van den Hout, T. Piersma, B. Kempenaers, D. Réale, and N. J. Dingemanse.
507 2011. Disentangling the roles of frequency-vs. state-dependence in generating individual
508 differences in behavioural plasticity. Ecology Letters 14:1254–1262.

509 McKinnon, L., and J. Béty. 2009. Effect of camera monitoring on survival rates of High-Arctic
510 shorebird nests. *Journal of Field Ornithology* 80:280–288.

511 Menge, B. A., and J. P. Sutherland. 1976. Species diversity gradients: synthesis of the roles of
512 predation, competition, and temporal heterogeneity. *The American Naturalist* 110:351–369.

513 Michelot, T., R. Langrock, and T. A. Patterson. 2016. moveHMM: an R package for the
514 statistical modelling of animal movement data using hidden Markov models. *Methods in
515 Ecology and Evolution* 7:1308–1315.

516 Montgomerie, R. D., and P. J. Weatherhead. 1988. Risks and rewards of nest defence by parent
517 birds. *The Quarterly Review of Biology* 63:167–187.

518 Morosinotto, C., R. L. Thomson, and E. Korpimäki. 2010. Habitat selection as an antipredator
519 behaviour in a multi-predator landscape: all enemies are not equal. *Journal of Animal Ecology*
520 79:327–333.

521 Patterson, T. A., A. Parton, R. Langrock, P. G. Blackwell, L. Thomas, and R. King. 2017.
522 Statistical modelling of individual animal movement: an overview of key methods and a
523 discussion of practical challenges. *AStA Advances in Statistical Analysis* 101:399–438.

524 Peluc, S. I., T. S. Sillett, J. T. Rotenberry, and C. K. Ghalambor. 2008. Adaptive phenotypic
525 plasticity in an island songbird exposed to a novel predation risk. *Behavioral Ecology* 19:830–
526 835.

527 Poulin, M. P., J. Clermont, and D. Berteaux. 2020. Extensive daily movement rates measured in
528 territorial arctic foxes. *Ecology and Evolution*, under review (accepted with minor revisions).

529 QGIS Development Team. 2019. QGIS Geographic Information System, Open Source
530 Geospatial Foundation Project.

531 R Development Team. 2019. R: a language and environment for statistical computing. R
532 Foundation for Statistical Computing, Vienna, Austria.

533 Reed, A., R. J. Hughes, and G. Gauthier. 1995. Incubation behavior and body mass of female
534 greater snow geese. *The Condor* 97:993–1001.

535 Rosenbaum, S. 2018. Offspring defense. *in* T. K. Shackelford, and V. A. Weekes-Shackelford,
536 editors. *Encyclopedia of evolutionary psychological sciences*. Springer, Cham, Switzerland.

537 Schielzeth, H. 2010. Simple means to improve the interpretability of regression coefficients.
538 *Methods in Ecology and Evolution* 1:103–113.

539 Schmitz, O. J., V. Krivan, and O. Ovadia. 2004. Trophic cascades: the primacy of trait-mediated
540 indirect interactions. *Ecology Letters* 7:153–163.

541 Stephens, D. W., and J. R. Krebs. 1986. *Foraging theory*. Princeton University Press, Princeton,
542 N.J., USA.

543 Teckentrup, L., V. Grimm, S. Kramer-Schadt, and F. Jeltsch. 2018. Community consequences of
544 foraging under fear. *Ecological Modelling* 383:80–90.

545 Thaker, M., A. T. Vanak, C. R. Owen, M. B. Ogden, S. M. Niemann, and R. Slotow. 2011.
546 Minimizing predation risk in a landscape of multiple predators: effects on the spatial
547 distribution of African ungulates. *Ecology* 92:398–407.

548 Therneau, T. M., T. Lumley, E. Atkinson, and C. Crowson. 2020. *survival: Survival Analysis*. R
549 package version 3.1-11. <https://CRAN.R-project.org/package=survival>

550 Willems, E. P., and R. A. Hill. 2009. Predator-specific landscapes of fear and resource
551 distribution: effects on spatial range use. *Ecology* 90:546–555.

552 Wilmers, C. C., B. Nickel, C. M. Bryce, J. A. Smith, R. E. Wheat, and V. Yovovich. 2015. The
553 golden age of bio-logging: how animal-borne sensors are advancing the frontiers of ecology.
554 *Ecology* 96:1741–1753.

555 Ydenberg, R. C., and L. M. Dill. 1986. The economics of fleeing from predators. *Advances in*
556 *the Study of Behavior* 16:229–249.

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Appendix S1 – Supplementary tables and figures

Table S1. Number of GPS fixes obtained for 13 arctic foxes tracked during 10 days at the end of June 2019 on Bylot Island (Nunavut, Canada). The tag code, ID (also indicating sex, M: male, F: female) and territory color (see Fig. 1) are given for each fox. GPS fixes were assigned an active or resting state using a hidden Markov model (HMM). Fixes with unknown location (time-outs) due to missing connection with satellites, which mostly occurred when foxes were inside their den, were excluded from analyses. The number of fixes per individual was nearly 3600 (10 days at a 4-min fix interval) for all foxes except F3 (due to a battery failure).

Tag code	ID	Territory	Number of GPS fixes			
			Total	Active state	Resting state	Time-out
OBOB	M1	orange	3569	1484 (42%)	1886 (53%)	199 (5%)
JVOJ	F1	orange	3561	1096 (31%)	1006 (28%)	1459 (41%)
BORR	M2	gray	3562	1438 (40%)	1856 (52%)	268 (8%)
RMJJ	F2	gray	3572	1200 (33%)	2311 (65%)	61 (2%)
OBBB	M3	green	3550	1805 (51%)	1511 (42%)	234 (7%)
JMVJ	F3	green	2674	1021 (38%)	1485 (56%)	168 (6%)
VJOO	M4	pink	3567	1840 (51%)	1594 (45%)	133 (4%)
BVOB	F4	pink	3564	2087 (59%)	819 (23%)	658 (18%)
RVJO	M5	dark blue	3572	1994 (56%)	1554 (43%)	24 (1%)
OJOO	F5	dark blue	3240	1646 (51%)	966 (30%)	628 (19%)
ORRR	M6	light blue	3568	2136 (60%)	1430 (40%)	2 (0%)
RMBR	F6	light blue	3569	1637 (46%)	1694 (47%)	238 (7%)
BBJO	M7	red	3572	1577 (44%)	1946 (55%)	49 (1%)

Table S2. Variance values for random effects of binomial mixed models testing the effect of fox UD score on the probability of predation of baits, with patch ID nested in territory ID fitted as random effects, for the 5 UD s with smoothing parameter ranging from 200 to 400 m (n = 428 baits).

UD smoothing parameter (m)	Random effect	Variance	SD
200	Patch: territory	0.40	0.63
	Territory	0.65	0.81
250	Patch: territory	0.39	0.63
	Territory	0.64	0.80
300	Patch: territory	0.38	0.62
	Territory	0.64	0.80
350	Patch: territory	0.37	0.61
	Territory	0.64	0.80
400	Patch: territory	0.37	0.61
	Territory	0.65	0.81

Table S3. Variance values for random effects of linear mixed models testing the effect of fox UD score on goose flushing distance, with territory ID and observer ID fitted as random effects, for the 5 UD s with smoothing parameter ranging from 200 to 400 m (n = 458 goose nests).

UD smoothing parameter (m)	Random effect	Variance	SD
200	Territory	1.44	1.20
	Observer	0.10	0.32
	Residuals	3.78	1.94
250	Territory	1.44	1.20
	Observer	0.10	0.31
	Residuals	1.38	1.94
300	Territory	1.39	1.18
	Observer	0.10	0.31
	Residuals	3.79	1.95
350	Territory	1.34	1.16
	Observer	0.10	0.32
	Residuals	3.80	1.95
400	Territory	1.29	1.14
	Observer	0.10	0.32
	Residuals	3.81	1.95

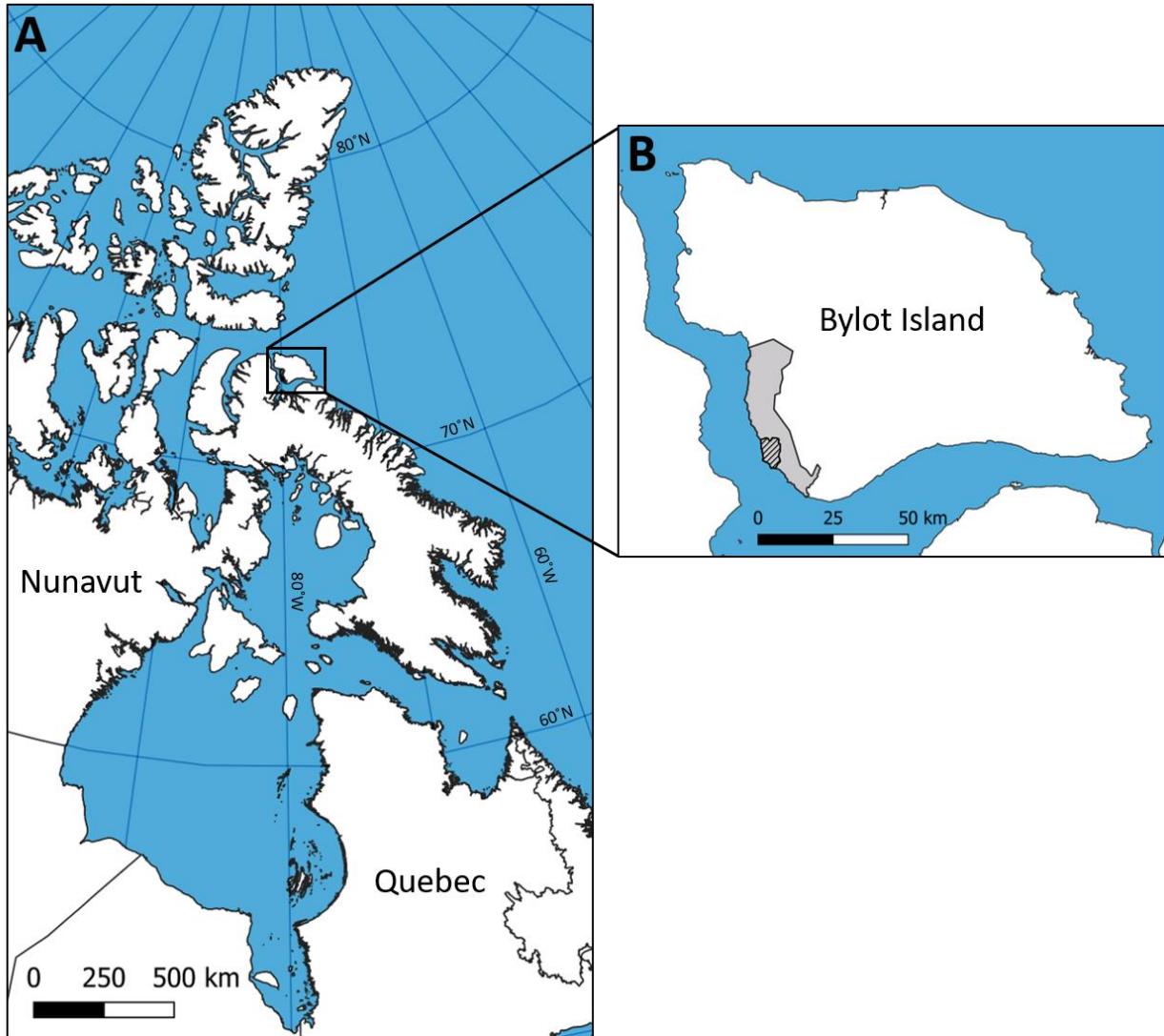


Fig. S1. Geographical context of the study area. Panel A locates Bylot Island ($72^{\circ}53' \text{ N}$, $79^{\circ}54' \text{ W}$) in Nunavut, Canada, which is enlarged in B. The hatched area depicts our study area containing 6 arctic fox territories used by 6 fox pairs and one additional individual (Fig. 1), while the larger gray area depicts Bylot Island's entire field site.

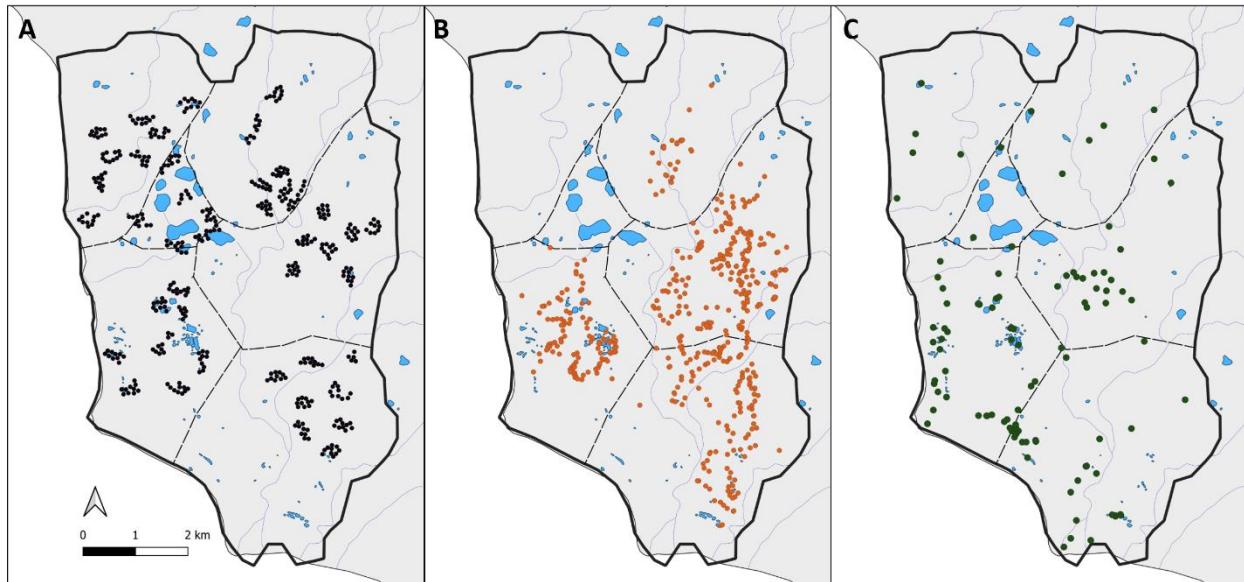


Fig. S2. Distribution of A) fox baits used in the artificial prey experiment (n = 428, black dots), B) nests used to evaluate snow goose anti-predator behavior (n = 458, orange dots), and C) nests of fox incidental prey, that is birds other than snow geese (n = 109, green dots). The dotted lines show the approximate boundaries of fox pair territories while the thick black line is the contour of the study area. Lakes and large ponds are in blue.

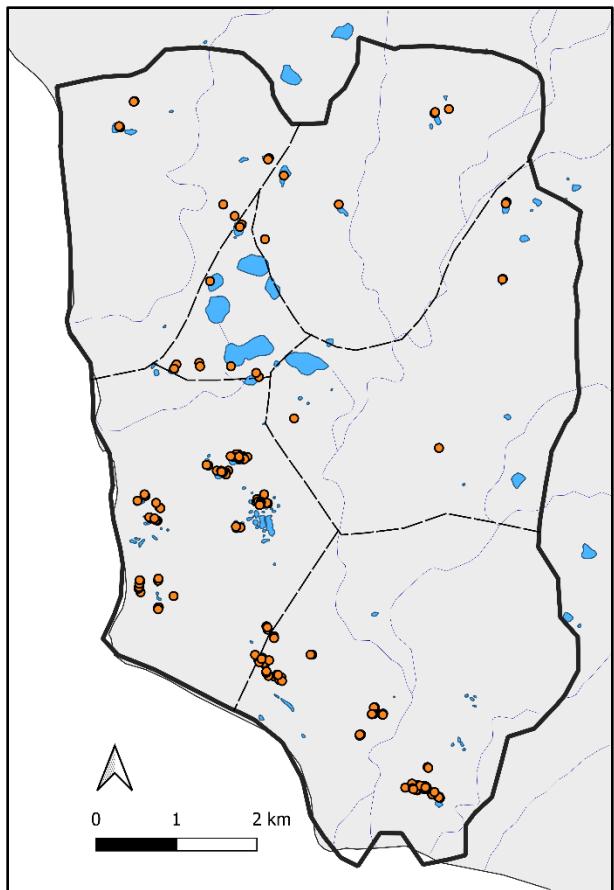


Fig. S3. Distribution of the 377 islets (orange dots) located in ponds, lakes and wetlands. Many dots are superimposed at this spatial scale. The dotted lines show the approximate boundaries of fox pair territories while the thick black line is the contour of the study area. Lakes and large ponds are in blue.

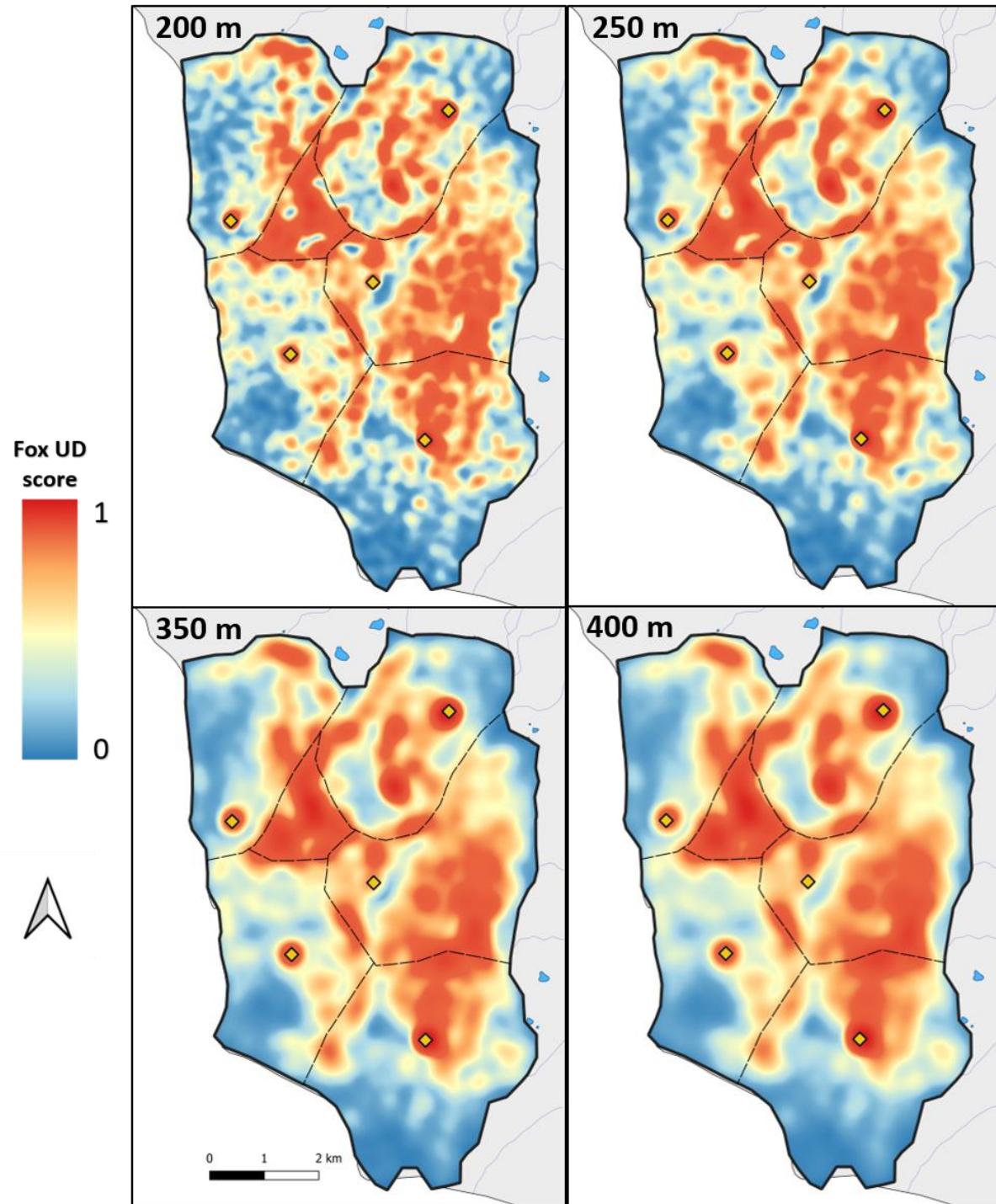


Fig. S4. Arctic fox activity landscapes generated from 20,961 GPS locations classified in the active state by a hidden Markov model, using UD smoothing parameters ranging from 200 to 400 m, as indicated on the top left corner of each map (see Fig. 2 in the main text for activity

landscape using the intermediate smoothing parameter of 300 m). The activity landscape reflects fox utilization distribution (UD) based on data from 13 individuals living in 6 territories during 10 days at the end of June 2019 on Bylot Island. The color scale reflects fox UD score (from 0 to 1) and thus probability of presence of a fox. Yellow diamonds locate the 5 reproductive dens, dotted lines identify the approximate boundaries of fox pair territories, and the thick black line is the contour of the study area.

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Appendix S2 – Complementary analyses for distribution of birds nesting in refuges

The number of available islets per nest varied according to the radius of the nest area, with 26 ± 12 (range 3–50) available islets for a radius of 1000 m, 40 ± 12 (3–50) for 1500 m, 46 ± 10 (3–50) for 2000 m, 47 ± 9 (9–50) for 1500 m and 48 ± 7 (10–50) for 3000 m. Results from these models are presented in Table 3 (main text).

We conducted two complementary analyses to verify whether using an unbalanced number of available locations affected results. First, we compared fox UD scores at bird nests to fox UD scores at available islets as described in Methods (3-Nest distribution of incidental prey/Second set of models), but using more balanced sample sizes of ≤ 10 islets instead of ≤ 50 . We could not use a totally balanced design as the minimum number of islets was only 3. Obtained results (Table S1) did not differ from those presented in the main text (Table 3).

Second, we compared fox UD scores at bird nests to fox UD scores at available locations as described in Methods (3-Nest distribution of incidental prey/First set of models), thus comparing UD scores of used islets to 50 random locations picked anywhere in the nest area, excluding water bodies (this yielded a balanced design). An advantage of this approach is that it also allowed us to verify whether drawing available locations from georeferenced islets rather than anywhere in the nest area affected our conclusions. Results (Table S2) did not differ from those presented in the main text (Table 3).

Table S1. Results from conditional logistic regressions with a use-available design testing the effect of fox UD score on the nest distribution of birds that nest in micro-habitats providing partial refuge against foxes (n = 65 nests from 3 species). The fox UD score of each nest was compared to the fox UD score of ≤ 10 islets surrounding the nest within the nest area. Coefficient estimates are presented for 25 models, each reflecting a given size of the nest area (from 1000 to 3000 m) and UD smoothing parameter (from 200 to 400 m).

Radius of nest area (m)	UD smoothing parameter (m)	Coefficient [95% CI]	z value	p value
1000	200	0.41 [-7.95, 8.76]	0.10	0.924
	250	0.32 [-6.37, 7.01]	0.09	0.926
	300	0.18 [-5.47, 5.82]	0.06	0.952
	350	-0.02 [-4.97, 4.94]	-0.01	0.995
	400	-0.21 [-4.70, 4.27]	-0.09	0.926
1500	200	2.04 [-4.16, 8.24]	0.64	0.519
	250	1.41 [-3.40, 6.21]	0.57	0.566
	300	0.89 [-3.06, 4.85]	0.44	0.658
	350	0.50 [-2.87, 3.89]	0.29	0.771
	400	0.24 [-2.77, 3.24]	0.15	0.878
2000	200	4.12 [-1.67, 9.91]	1.40	0.163
	250	2.90 [-1.54, 7.33]	1.28	0.201
	300	2.06 [-1.59, 5.70]	1.11	0.269
	350	1.52 [-1.59, 4.63]	0.96	0.338
	400	1.20 [-1.53, 3.93]	0.86	0.390
2500	200	3.75 [-1.88, 9.39]	1.31	0.192
	250	2.74 [-1.56, 7.05]	1.25	0.211
	300	2.10 [-1.41, 5.62]	1.17	0.241
	350	1.66 [-1.34, 4.66]	1.08	0.278
	400	1.33 [-1.30, 3.98]	0.99	0.321
3000	200	3.04 [-2.35, 8.42]	1.11	0.269
	250	2.14 [-1.96, 6.23]	1.02	0.307
	300	1.49 [-1.87, 4.84]	0.87	0.385
	350	1.01 [-1.85, 3.86]	0.69	0.488
	400	0.69 [-1.81, 3.19]	0.54	0.589

Table S2. Results from conditional logistic regressions with a use-available design testing the effect of fox UD score on the nest distribution of birds that nest in micro-habitats providing partial refuge against foxes (n = 65 nests from 3 species). The fox UD score of each nest was compared to the fox UD scores of 50 random locations surrounding the nest within the nest area. Coefficient estimates are presented for 25 models, each reflecting a given size of the nest area (from 1000 to 3000 m) and UD smoothing parameter (from 200 to 400 m). Significant effects are in bold.

Radius of nest area (m)	UD smoothing parameter (m)	Coefficient [95% CI]	z value	p value
1000	200	2.91 [-0.83, 6.65]	1.52	0.128
	250	3.01 [-0.06, 6.09]	1.92	0.055
	300	3.03 [0.33, 5.74]	2.20	0.028
	350	2.97 [0.51, 5.43]	2.36	0.018
	400	2.81 [0.50, 5.12]	2.39	0.017
1500	200	2.56 [-1.05, 6.18]	1.39	0.165
	250	2.55 [-0.36, 5.47]	1.72	0.086
	300	2.48 [-0.05, 5.00]	1.92	0.054
	350	2.32 [0.05, 4.58]	2.01	0.045
	400	2.08 [-0.001, 4.17]	1.96	0.050
2000	200	-0.005 [-3.96, 3.95]	0.00	0.998
	250	0.17 [-2.90, 3.25]	0.11	0.912
	300	0.23 [-2.36, 2.82]	0.17	0.864
	350	0.19 [-2.10, 2.48]	0.16	0.870
	400	0.08 [-2.00, 2.16]	0.08	0.940
2500	200	-0.73 [-4.87, 3.42]	-0.34	0.731
	250	-0.39 [-3.64, 2.85]	-0.24	0.813
	300	-0.29 [-3.02, 2.45]	-0.21	0.836
	350	-0.31 [-2.71, 2.09]	-0.26	0.798
	400	-0.44 [-2.61, 1.73]	-0.40	0.690
3000	200	-2.61 [-7.21, 1.99]	-1.11	0.267
	250	-1.93 [-5.45, 1.58]	-1.08	0.281
	300	-1.61 [-4.49, 1.27]	-1.10	0.273
	350	-1.48 [-3.95, 0.99]	-1.17	0.241
	400	-1.48 [-3.67, 0.71]	-1.32	0.186