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Wildlife Research

Supplementary Material

Estimating habitat characteristics associated with the abundance of free-roaming domestic cats across the annual cycle

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Part 1: Additional details about detection and site covariates

To account for the possibility that cats may not be detected even if they were present at a camera site, we modelled detection probability using variables that could influence cat behaviour during the sampling occasions (McClintock and White 2012): time of year (Julian date), average temp (°C), average daily precip (mm), and baiting status of the camera site (Table 2). Time of year (Julian date) was included in the detection probability models because cats may not walk in view of the camera every day but may still be present in the area. Temperature was included because cats are less active during extreme temps and rainfall because cats normally take shelter from heavy rains (Churcher and Lawton 1987; Hall *et al.* 2000; Harper 2007; Goszczyński *et al.* 2009) and, therefore, are less likely to be recorded by the camera. We obtained temperature and precipitation data from the *weathercan* package in R (LaZerte and Albers 2018). We used the average temp and average daily precipitation over our 72-hr sampling period. Baiting status (baited or not-baited) was included to account for the possibility of increased detection on baiting days (du Preez *et al.* 2014).

The site covariates are associated with habitat characteristics that have been known to influence cat abundances and include buildings, roads, woodlots, agricultural land and neighbourhood income and the presence or absence of coyotes. The shapefiles for buildings were generated from aerial satellite photos from the 2020 Google Maps base map in QGIS. We did not include small sheds because these could not be consistently seen due to tree cover. We included barns, detached garages, and portables because these buildings offer cats protection from inclement weather and are likely to have food sources nearby (i.e. garbage). All buildings within a 100 m buffer around the trail camera were traced, with three exceptions: 1) when the camera was directly beside a building(s), in which only the adjacent buildings were tranced, 2) when the camera was in a residential backyard, in which only the buildings on the same block were traced, and 3) when there were no buildings within a 100 m buffer around the camera. In this case, the buffer was extended to 500 m. The shapefiles for major roads was generated from using a subsection of geospatial data of the road network within the study area (Ontario Ministry of Natural Resources and Forestry 2019), and only included roads that were designated as “major” according to the Guelph 2018 arterial and collector street map (The City of Guelph 2018). We obtained geospatial data of the woodlots within the study areas from Ontario GeoHub (Smith 2018). We obtained geospatial data of the agricultural fields within the study areas that were in use (Ontario Ministry of Agriculture Food and Rural Affairs 2018). Since we are most interested in seasonal changes of the abundance of cats, we only included the shapefiles for fields, which are generally harvested in the fall, and excluded the shapefiles for fencerows and homesteads. We obtained the total median household income of each census block that had a trail camera from the 2016 Canadian census (Statistics Canada 2016).

References

Churcher, P. B., and Lawton, J. H. (1987). Predation by domestic cats in an English village. *Zoological Society of London* **212**, 439–455.

Goszczyński, J., Krauze, D., and Gryz, J. (2009). Activity and exploration range of house cats in rural areas of central Poland. *Folia Zoologica* **58**, 363–371.

Hall, L. S., Kasparian, M. A., Van Vuren, D., and Kelt, D. A. (2000). Spatial organization and habitat use of feral cats (Felis catus L) in Mediterranean California. *Mammalia* **64**, 19–28. doi:10.1515/mamm.2000.64.1.19

Harper, G. A. (2007). Habitat selection of feral cats (Felis catus) on a temperate, forested island. *Austral Ecology* **32**, 305–314. doi:10.1111/j.1442-9993.2007.01696.x

LaZerte, S., and Albers, S. (2018). weathercan: Download and format weather data from Environment and Climate Change Canada. *The Journal of Open Source Software* **3**, 571. Available at: http://joss.theoj.org/papers/10.21105/joss.00571

McClintock, B. T., and White, G. C. (2012). From NOREMARK to MARK: Software for estimating demographic parameters using mark-resight methodology. *Journal of Ornithology* **152**, 641–650. doi:10.1007/s10336-010-0524-x

Ontario Ministry of Agriculture Food and Rural Affairs (2018). Agricultural Resource Inventory (ARI) – Final – for years: 2017-2018: Farms, Fields, Fencecrows and Roughland. SGP_id: 1852251910. *SGP_id: 1852251910*. Available at: http://geo.scholarsportal.info/#r/details/_uri@=1852251910

Ontario Ministry of Natural Resources and Forestry (2019). Ontario Road Network Road Net Element. *Ontario GeoHub*. Available at: https://geohub.lio.gov.on.ca/datasets/mnrf::ontario-road-network-orn-road-net-element?geometry=-79.825%2C43.688%2C-79.780%2C43.698 [accessed 23 July 2019]

du Preez, B. D., Loveridge, A. J., and Macdonald, D. W. (2014). To bait or not to bait: a comparison of camera-trapping methods for estimating leopard Panthera pardus density. *Biological Conservation* **176**, 153–161.

Smith, K. (2018). Wooded Area. *Ontario GeoHub*. Available at: https://geohub.lio.gov.on.ca/datasets/wooded-area [accessed 30 September 2019]

Statistics Canada (2016). Household Income Statistics (3) and Household Type Including Census Family Structure (11) for Private Households of Census Metropolitan Areas, Tracted Census Agglomerations and Census Tracts, 2016 Census - 100% Data. *Statistics Canada*, Catalogue number : 98-400-X2016100.

The City of Guelph (2018). Arterial and collector street map. Available at: http://guelph.ca/wp-%0Acontent/uploads/map_CityOfGuelph.pdf

Part 2: R code

AIC$_c$ and relative importance analysis

The same R code was used for both the spring/summer and fall/winter period of the year and can be found below.

```
>> library(unmarked)

>> library(MuMIn)

>> cat.abun.ss.<-read.csv("~/Desktop/Guelph Cat research/My Cat R
Code/Abundance/abun-s-s.csv")

>> y.abun.ss.<-cat.abun.ss.[3:6]

>> siteCovs.ss <- cat.abun.ss.[c(1,2,23:33)]

>> obsCovs.ss <- list(date=cat.abun.ss.[7:10],
        AVtemp=cat.abun.ss.[11:14],
        Precip=cat.abun.ss.[15:18],
        Bait=cat.abun.ss.[19:22])

>> cat.abun.ss.1<-unmarkedFramePCount(y=y.abun.ss., siteCovs = siteCovs.ss,
obsCovs = obsCovs.ss)

>> cat.abun.ss.1@siteCovs$distance_maj_road <-
    scale(cat.abun.ss.1@siteCovs$distance_maj_road)

>> cat.abun.ss.1@siteCovs$distance_wood <-
    scale(cat.abun.ss.1@siteCovs$distance_wood)

>> cat.abun.ss.1@siteCovs$distance_agro <-
```

```
        scale(cat.abun.ss.1@siteCovs$distance_agro)
>> cat.abun.ss.1@siteCovs$dist_building <-
        scale(cat.abun.ss.1@siteCovs$dist_building)
>> cat.abun.ss.1@siteCovs$income <- scale(cat.abun.ss.1@siteCovs$income)
>> cat.abun.ss.1@siteCovs$Coyote <- as.factor(cat.abun.ss.1@siteCovs$Coyote)
>> cat.abun.ss.1@obsCovs$date <- scale(cat.abun.ss.1@obsCovs$date)
>> cat.abun.ss.1@obsCovs$AVtemp <- scale(cat.abun.ss.1@obsCovs$AVtemp)
>> cat.abun.ss.1@obsCovs$Precip <- scale(cat.abun.ss.1@obsCovs$Precip)
>> cat.abun.ss.1@obsCovs$Bait <- as.factor(cat.abun.ss.1@obsCovs$Bait)
>> summary(cat.abun.ss.1)
>> abun.ss.full<-pcount(~AVtemp+Bait+Precip+date
        ~dist_building+ income+ distance_agro+ distance_wood+ distance_maj_road+
        Coyote, cat.abun.ss.1,mixture="NB", K=107,se=TRUE)
>> vif(abun.ss.full, type="state")
>> vif(abun.ss.full, type="det")
>> gof.global.ss.full <- Nmix.gof.test(abun.ss..full, nsim = 1000,plot.hist = TRUE,
        report = NULL)
>> abun.ss.det<- pcount(~AVtemp+Bait+Precip+date~1, cat.abun.ss.1,mixture="NB",
        K=107,se=TRUE)
>> model.list.abun.ss.det<-dredge(abun.ss.det, evaluate = TRUE)
>> sw(model.list.abun.ss.det)
```

```
>> abun.ss.state<- pcount(~date~dist_building+income+distance_agro+
        distance_wood+distance_maj_road+Coyote, cat.abun.ss.1,mixture="NB",
        K=107,se=TRUE)
>> gof.global.ss.<-Nmix.gof.test(abun.ss.state, nsim = 1000,plot.hist = TRUE,
        report = NULL)
>> model.list.abun.ss.state<-dredge(abun.ss..state, evaluate = TRUE, fixed = "p(date)")
>> sw(model.list.abun.ss..state)
>> ss.top.state.<-pcount(~AVtemp~dist_building+distance_agro,
        cat.abun.ss.1,mixture="NB", K=107,se=TRUE)
>> gof.top.ss.<-Nmix.gof.test(ss.top.state., nsim = 200,plot.hist = TRUE, report = NULL)
```

Landscape type analysis: linear mixed model

```
>> library(lme4)

>> library(lmerTest)

>> lin.mod.season.class<-read.csv("~/Desktop/Guelph Cat research/My Cat R
Code/Other tests/lin.mod.season.csv")

>> season.class.cat.mod <- lmerTest::lmer(Abun~Season*Land + (1|Site), data=
lin.mod.season.class)

>> qqnorm(resid(season.class.cat.mod))

>> qqline(resid(season.class.cat.mod))

>> boxplot(Abun ~ Land*Season, data = lin.mod.season.class)

>> summary(season.class.cat.mod)
```

Part 3: AIC_c Model Selection

Table S1. Variance inflation factors (VIF) for detection and abundance global models in both periods of the year. VIF values ≥ 5 indicate high multicollinearity. The global model for both periods was $p^{\text{(temp + date + precip + bait)}}\,\lambda^{\text{(buildings + roads + agriculture + woods + income + coyotes)}}$. See Table 2 in main text for descriptions of covariates.

Variable	Variance Inflation Factor	
	Spring/Summer	Fall/Winter
temp	1.63	2.64
date	1.50	2.13
precip	1.14	1.44
bait	1.01	1.02
buildings	1.39	1.57
roads	1.53	1.61
agriculture	1.73	2.06
woods	1.47	1.25
income	1.36	1.50
coyotes	1.26	1.21

Table S2. Comparison of detection probability (*p*) models based on the number of cats at a camera site during the spring/summer of 2018 in Wellington county, ON Canada. The global model was $p^{(\text{temp + date + precip + bait})}$ $\lambda^{(.)}$, where $\lambda^{(.)}$ represents the null local abundance sub-model. See Table 2 in the main document for descriptions of covariates.

Models	df	logLik	AIC_c	ΔAIC_c	weight
p (date) λ(.)	4	-164.71	338.21	0.00	0.19
p (temp) λ(.)	4	-164.85	338.50	0.29	0.16
p (.) λ(.)	3	-166.10	338.67	0.46	0.15
p (temp + date) λ(.)	5	-164.39	340.00	1.79	0.08
p (temp + precip) λ(.)	5	-164.54	340.31	2.10	0.06
p (date + precip λ(.)	5	-164.66	340.55	2.34	0.06
p (bait + date) λ(.)	5	-164.67	340.57	2.36	0.06
p (temp + bait) λ(.)	5	-164.79	340.81	2.60	0.05
p (precip) λ(.)	4	-166.06	340.93	2.72	0.05
p (bait) λ(.)	4	-166.10	341.00	2.79	0.05
p (temp + date + precip) λ(.)	6	-164.20	342.16	3.95	0.03
p (temp + bait + date) λ(.)	6	-164.32	342.39	4.18	0.02
p (temp + bait + precip) λ(.)	6	-164.48	342.70	4.50	0.02
p (bait + date + precip) λ(.)	6	-164.63	343.01	4.80	0.02
p (bait + precip) λ(.)	5	-166.06	343.35	5.14	0.01
p (temp + bait + date + precip) λ(.)	7	-164.13	344.64	6.43	0.01

Table S3. Comparison of local abundance (λ) models based on the number of cats at a camera site during the spring/summer of 2018 in Wellington county, ON, Canada. The global model was $p^{\text{(date)}}\ \lambda^{\text{(buildings + roads + agriculture + woodlots + income + coyotes)}}$. See Table 2 in the main document for descriptions of covariates.

Models	df	logLik	AIC_c	ΔAIC_c	weight
p (date) λ (building + agriculture)	6	-150.92	315.58	0.00	0.22
p (date) λ (building + agriculture + woods)	7	-150.57	317.52	1.94	0.08
p (date) λ (building + agriculture + income)	7	-150.62	317.62	2.04	0.08
p (date) λ (building + agriculture + roads)	7	-150.73	317.84	2.26	0.07
p (date) λ (building + woods)	6	-152.13	318.01	2.43	0.06
p (date) λ (coyote + building + agriculture)	7	-150.85	318.09	2.51	0.06
p (date) λ (building	5	-153.86	318.94	3.36	0.04
p (date) λ (building + roads)	6	-152.90	319.54	3.96	0.03
p (date) λ (building + agriculture + woods + income)	8	-150.21	319.56	3.98	0.03
p (date) λ (building + roads + woods)	7	-151.69	319.77	4.19	0.03
p (date) λ (building + agriculture + roads + income)	8	-150.33	319.79	4.21	0.03
p (date) λ (coyote + building + agriculture + woods)	8	-150.37	319.88	4.30	0.03
p (date) λ (building + agriculture + roads + woods)	8	-150.43	319.99	4.41	0.02
p (date) λ (coyote + building + agriculture + income)	8	-150.46	320.04	4.46	0.02
p (date) λ (coyote + building + woods)	7	-152.03	320.44	4.86	0.02
p (date) λ (coyote + building + agriculture + roads)	8	-150.69	320.51	4.93	0.02
p (date) λ (building + woods + income)	7	-152.10	320.58	5.00	0.02
p (date) λ (building + income)	6	-153.80	321.34	5.76	0.01
p (date) λ (coyote + building)	6	-153.85	321.45	5.87	0.01
p (date) λ (coyote + building + agriculture + woods + income)	9	-149.77	321.54	5.96	0.01
p (date) λ (building + agriculture + roads + woods + income)	9	-149.98	321.97	6.39	0.01

p (date) λ (coyote + building + roads)	7	-152.86	322.10	6.52	0.01
p (date) λ (building + roads + income)	7	-152.89	322.17	6.59	0.01
p (date) λ (agriculture) + roads)	6	-154.24	322.22	6.64	0.01
p (date) λ (building + roads + woods + income)	8	-151.59	322.31	6.73	0.01
p (date) λ (coyote + building + agriculture + roads + income)	9	-150.20	322.41	6.83	0.01
p (date) λ (coyote + building + roads + woods)	8	-151.65	322.42	6.84	0.01
p (date) λ (coyote + building + agriculture + roads + woods)	9	-150.29	322.57	6.99	0.01
p (date) λ (coyote + building + woods + income)	8	-151.96	323.04	7.46	0.01
p (date) λ (agriculture) + roads + income)	7	-153.50	323.39	7.81	< 0.01
p (date) λ (coyote + building + income)	7	-153.78	323.95	8.37	< 0.01
p (date) λ (coyote + building + agriculture + roads + woods + income)	10	-149.61	324.21	8.63	< 0.01
p (date) λ (agriculture) + roads + woods)	7	-153.96	324.31	8.73	< 0.01
p (date) λ (coyote + agriculture + roads)	7	-154.02	324.42	8.84	< 0.01
p (date) λ (agriculture)	5	-156.80	324.81	9.23	< 0.01
p (date) λ (coyote + building + roads + income)	8	-152.86	324.85	9.27	< 0.01
p (date) λ (coyote + building + roads + woods + income)	9	-151.50	325.00	9.42	< 0.01
p (date) λ (coyote + agriculture + roads + income)	8	-153.05	325.23	9.65	< 0.01
p (date) λ (agriculture) + roads + woods + income)	8	-153.14	325.40	9.82	< 0.01
p (date) λ (roads + woods)	6	-155.92	325.59	10.01	< 0.01
p (date) λ (coyote + agriculture)	6	-155.98	325.72	10.14	< 0.01
p (date) λ (roads)	5	-157.32	325.86	10.28	< 0.01
p (date) λ (coyote + agriculture + roads + woods)	8	-153.54	326.22	10.64	< 0.01
p (date) λ (agriculture) + woods)	6	-156.32	326.40	10.82	< 0.01
p (date) λ (agriculture) + income)	6	-156.37	326.49	10.91	< 0.01
p (date) λ (coyote + agriculture + roads + woods + income)	9	-152.30	326.60	11.02	< 0.01
p (date) λ (coyote + agriculture + woods)	7	-155.13	326.64	11.06	< 0.01
p (date) λ (coyote + agriculture + income)	7	-155.25	326.88	11.30	< 0.01

p (date) λ (coyote + agriculture + woods + income)	8	-154.13	327.39	11.81	< 0.01
p (date) λ (roads + woods + income)	7	-155.64	327.66	12.08	< 0.01
p (date) λ (coyote + roads + woods)	7	-155.71	327.80	12.22	< 0.01
p (date) λ (agriculture) + woods + income)	7	-155.83	328.05	12.47	< 0.01
p (date) λ (roads + income)	6	-157.29	328.33	12.75	< 0.01
p (date) λ (coyote + roads)	6	-157.31	328.37	12.79	< 0.01
p (date) λ (coyote + roads + woods + income)	8	-155.30	329.73	14.15	< 0.01
p (date) λ (coyote + roads + income)	7	-157.28	330.95	15.37	< 0.01
p (date) λ (woods)	5	-160.78	332.78	17.20	< 0.01
p (date) λ (coyote + woods)	6	-159.53	332.82	17.24	< 0.01
p (date) λ (coyote + woods + income)	7	-159.37	335.11	19.53	< 0.01
p (date) λ (woods + income)	6	-160.75	335.25	19.67	< 0.01
p (date) λ (.)	4	-164.70	338.21	22.63	< 0.01
p (date) λ (coyote)	5	-164.02	339.26	23.68	< 0.01
p (date) λ (income)	5	-164.44	340.09	24.51	< 0.01
p (date) λ (coyote + income)	6	-163.84	341.42	25.84	< 0.01

Table S4. Comparison of detection probability (*p*) models based on the number of cats at a camera site during the fall/winter of 2018–2019 in Wellington county, ON, Canada. The global model was $p^{\text{(temp + date + precip + bait)}}\ \lambda^{(.)}$, where $\lambda^{(.)}$ represents the null local abundance sub-model. See Table 2 in the main document for descriptions of covariates.

Models	df	logLik	AIC_c	$\Delta\ AIC_c$	weight
p (date) λ (.)	4	-189.54	387.90	0.00	0.42
p (date + precip) λ (.)	5	-189.27	389.82	1.92	0.16
p (temp + date λ (.)	5	-189.44	390.15	2.25	0.14
p (bait + date λ (.)	5	-189.53	390.33	2.42	0.13
p (bait + date + precip) λ (.)	6	-189.27	392.36	4.46	0.05
p (temp + date + precip) λ (.)	6	-189.27	392.37	4.46	0.05
p (temp + bait + date λ (.)	6	-189.43	392.68	4.78	0.04
p (temp + bait + date + precip) λ (.)	7	-189.27	395.02	7.12	0.01
p (temp) λ (.)	4	-194.09	397.01	9.10	< 0.01
p (temp + precip) λ (.)	5	-193.97	399.21	11.31	< 0.01
p (temp + bait λ (.)	5	-194.06	399.40	11.50	< 0.01
p (temp + bait + precip) λ (.)	6	-193.94	401.70	13.79	< 0.01
p (.) λ (.)	3	-201.75	409.99	22.09	< 0.01
p (precip) λ (.)	4	-200.89	410.62	22.71	< 0.01
p (bait λ (.)	4	-201.75	412.32	24.42	< 0.01
p (bait + precip) λ (.)	5	-200.89	413.06	25.15	< 0.01

Table S5. Comparison of local abundance (λ) models based on the number of cats at a camera site during the fall/winter of 2018–2019 in Wellington county, ON, Canada. The global model was $p^{\text{(date)}}\ \lambda^{\text{(buildings + roads+ agriculture + woodlots + income + coyotes)}}$. See Table 2 in the main document for descriptions of covariates.

Models	df	logLik	AIC_c	ΔAIC_c	weight
p (date) λ (coyote + roads)	6	-176.20	366.22	0.00	0.21
p (date) λ (coyote + buildings + roads)	7	-175.71	367.91	1.69	0.09
p (date) λ (coyote + agriculture + roads)	7	-175.79	368.07	1.85	0.08
p (date) λ (coyote + roads + income)	7	-175.89	368.27	2.05	0.07
p (date) λ (coyote + roads + woods)	7	-176.15	368.78	2.56	0.06
p (date) λ (buildings + roads)	6	-177.81	369.44	3.22	0.04
p (date) λ (coyote + buildings + agriculture + roads)	8	-175.35	369.97	3.75	0.03
p (date) λ (coyote + buildings + roads + income)	8	-175.37	370.01	3.79	0.03
p (date) λ (buildings + agriculture + roads)	7	-176.94	370.38	4.16	0.03
p (date) λ (buildings + agriculture)	6	-178.33	370.48	4.27	0.02
p (date) λ (coyote + buildings + roads + woods)	8	-175.66	370.59	4.37	0.02
p (date) λ (coyote + agriculture + roads + income)	8	-175.73	370.73	4.51	0.02
p (date) λ (coyote + agriculture + roads + woods)	8	-175.79	370.86	4.64	0.02
p (date) λ (coyote + buildings + agriculture)	7	-177.26	371.01	4.79	0.02
p (date) λ (coyote + roads + woods + income)	8	-175.88	371.03	4.81	0.02
p (date) λ (buildings + roads + income)	7	-177.38	371.24	5.02	0.02
p (date) λ (coyote + buildings)	6	-178.71	371.25	5.04	0.02
p (date) λ (agriculture + roads)	6	-178.96	371.74	5.52	0.01
p (date) λ (roads)	5	-180.28	371.85	5.63	0.01
p (date) λ (buildings + roads + woods)	7	-177.71	371.91	5.69	0.01
p (date) λ (buildings)	5	-180.34	371.95	5.74	0.01
p (date) λ (coyote + buildings + income)	7	-177.87	372.23	6.02	0.01

p (date) λ (buildings + income)	6	-179.43	372.68	6.46	0.01
p (date) λ (coyote + buildings + agriculture + roads + income)	9	-175.25	372.69	6.48	0.01
p (date) λ (coyote + agriculture	6	-179.53	372.88	6.66	0.01
p (date) λ (coyote + buildings + agriculture + roads + woods)	9	-175.35	372.88	6.66	0.01
p (date) λ (coyote + buildings + roads + woods + income)	9	-175.36	372.90	6.69	0.01
p (date) λ (coyote + buildings + woods)	7	-178.25	372.99	6.78	0.01
p (date) λ (buildings + agriculture + income)	7	-178.29	373.07	6.85	0.01
p (date) λ (buildings + agriculture + roads + income)	8	-176.91	373.09	6.87	0.01
p (date) λ (buildings + agriculture + woods)	7	-178.31	373.11	6.89	0.01
p (date) λ (buildings + agriculture + roads + woods)	8	-176.94	373.16	6.94	0.01
p (date) λ (buildings + woods)	6	-179.83	373.50	7.28	0.01
p (date) λ (coyote + buildings + agriculture + income)	8	-177.18	373.63	7.42	0.01
p (date) λ (coyote + agriculture + roads + woods + income)	9	-175.73	373.64	7.42	0.01
p (date) λ (coyote + buildings + agriculture + woods)	8	-177.22	373.72	7.50	< 0.01
p (date) λ (roads + income)	6	-179.98	373.78	7.56	< 0.01
p (date) λ (buildings + roads + woods + income)	8	-177.35	373.97	7.75	< 0.01
p (date) λ (roads + woods)	6	-180.14	374.11	7.90	< 0.01
p (date) λ (agriculture + roads + income)	7	-178.95	374.40	8.18	< 0.01
p (date) λ (agriculture + roads + woods)	7	-178.95	374.40	8.18	< 0.01
p (date) λ (coyote + buildings + woods + income)	8	-177.68	374.62	8.41	< 0.01
p (date) λ (buildings + woods + income)	7	-179.20	374.90	8.68	< 0.01
p (date) λ (coyote + agriculture + woods)	7	-179.48	375.44	9.22	< 0.01
p (date) λ (coyote + agriculture + income)	7	-179.51	375.51	9.30	< 0.01
p (date) λ (coyote + buildings + agriculture + roads + woods + income)	10	-175.25	375.74	9.53	< 0.01
p (date) λ (buildings + agriculture + woods + income)	8	-178.27	375.82	9.60	< 0.01
p (date) λ (buildings + agriculture + roads + woods + income)	9	-176.91	376.00	9.78	< 0.01

p (date) λ (coyote)	5	-182.45	376.18	9.96	< 0.01
p (date) λ (roads + woods + income)	7	-179.91	376.31	10.09	< 0.01
p (date) λ (coyote + buildings + agriculture + woods + income)	9	-177.15	376.48	10.27	< 0.01
p (date) λ (coyote + income)	6	-181.35	376.53	10.32	< 0.01
p (date) λ (coyote + woods)	6	-181.59	377.01	10.79	< 0.01
p (date) λ (agriculture + roads + woods + income)	8	-178.95	377.18	10.96	< 0.01
p (date) λ (agriculture)	5	-183.38	378.03	11.82	< 0.01
p (date) λ (coyote + agriculture + woods + income)	8	-179.47	378.20	11.99	< 0.01
p (date) λ (coyote + woods + income)	7	-180.90	378.29	12.07	< 0.01
p (date) λ (agriculture + woods)	6	-183.32	380.47	14.25	< 0.01
p (date) λ (agriculture + income)	6	-183.34	380.50	14.28	< 0.01
p (date) λ (agriculture + woods + income)	7	-183.27	383.03	16.82	< 0.01
p (date) λ (woods)	5	-187.83	386.93	20.71	< 0.01
p (date) λ (income)	5	-188.22	387.72	21.50	< 0.01
p (date) λ (.)	4	-189.54	387.90	21.69	< 0.01
p (date) λ (woods + income)	6	-187.11	388.05	21.83	< 0.01

Table S6. The relative importance of the detection variables from the AIC_c model selection. The relative importance of each variable is calculated by adding the weighting of each model in which the variable appears and can range from 0 to 1, with higher summed weights indicating more relatively important variables. See Table 2 in the main document for descriptions of covariates.

Variable	Period of the year	
	Spring/Summer	Fall/Winter
date	0.45	0.99
temp	0.43	0.24
precip	0.25	0.27
bait	0.23	0.22

Table S7. The relative importance of the habitat characteristics from the AIC_c local abundance model selection. The relative importance of each variable is calculated by adding the weighting of each model in which the variable appears and can range from 0 to 1, with higher summed weights indicating more relatively important variables.

Variable	Period of the year	
	Spring/Summer	Fall/Winter
Distance to buildings (m)	0.96	0.45
Distance to major roads (m)	0.29	0.85
Presence of coyotes	0.23	0.77
Distance to agricultural land (m)	0.73	0.32
Distance to woodlots (m)	0.35	0.21
Median household income (CAD)	0.26	0.25

Part 4: Results from the Spring/Summer trail camera analysis and comparison between trail cameras and distance-based walking transect survey methods

Table S8. Detection probability (*p*) models based on the number of cats at urban sites within the city of Guelph, ON Canada, from the spring/summer of 2018. Models were ranked using AIC_c. The global model was $p^{(\text{temp + bait + date + precip})}\ \lambda^{(.)}$, where $\lambda^{(.)}$ represents the null local abundance sub-model. See Table 2 in the main document for descriptions of covariates.

Models	df	logLik	AIC_c	ΔAIC_c	weight
p (date) λ (.)	4	-111.77	233.21	0.00	0.31
p (.) λ (.)	3	-114.11	235.18	1.97	0.12
p (temp) λ (.)	4	-112.77	235.22	2.01	0.11
p (bait + date) λ (.)	5	-111.46	235.52	2.31	0.10
p (temp + date) λ (.)	5	-111.68	235.98	2.77	0.08
p (date + precip) λ (.)	5	-111.76	236.12	2.91	0.07
p (temp + bait λ (.)	5	-112.50	237.60	4.39	0.03
p (bait λ (.)	4	-113.99	237.64	4.43	0.03
p (temp + precip) λ (.)	5	-112.54	237.68	4.47	0.03
p (precip) λ (.)	4	-114.09	237.85	4.64	0.03
p (temp + bait + date) λ (.)	6	-111.34	238.50	5.30	0.02
p (bait + date + precip) λ (.)	6	-111.43	238.68	5.47	0.02
p (temp + date + precip) λ (.)	6	-111.62	239.06	5.85	0.02
p (temp + bait + precip) λ (.)	6	-112.21	240.24	7.03	0.01
p (bait + precip) λ (.)	5	-113.97	240.54	7.33	0.01
p (temp + bait + date + precip) λ (.)	7	-111.26	241.84	8.63	< 0.01

Table S9. Local abundance (λ) models based on cats at urban sites within the city of Guelph, ON Canada, from the spring/summer of 2018. Models were ranked using AIC_c. The global model was $p^{\,(date)}\lambda^{(buildings\,+\,roads\,+\,woods\,+\,income)}$. See Table 2 for descriptions of covariates.

Models	df	logLik	AIC_c	ΔAIC_c	weight
p (date) λ (buildings + income)	6	-107.33	230.48	0.00	0.19
p (date) λ (buildings + woods)	6	-107.46	230.74	0.25	0.17
p (date) λ (buildings)	5	-109.20	231.00	0.52	0.15
p (date) λ (buildings + woods + income)	7	-106.06	231.45	0.97	0.12
p (date) λ (buildings + roads + income)	7	-106.57	232.47	1.99	0.07
p (date) + woods)	5	-110.05	232.71	2.23	0.06
p (date)	4	-111.77	233.21	2.73	0.05
p (date) λ (income)	5	-110.73	234.07	3.58	0.03
p (date) λ (buildings + roads)	6	-109.19	234.21	3.72	0.03
p (date) λ (buildings + roads + woods + income)	8	-105.51	234.23	3.74	0.03
p (date) λ (buildings + roads + woods)	7	-107.46	234.25	3.76	0.03
p (date) λ (woods + income)	6	-109.41	234.64	4.16	0.02
p (date) λ (roads + woods)	6	-110.04	235.90	5.42	0.01
p (date) λ (roads	5	-111.73	236.07	5.59	0.01
p (date) λ (roads + income)	6	-110.69	237.20	6.72	0.01
p (date) λ (roads + woods + income)	7	-109.34	238.01	7.52	< 0.01

Table S10. Comparison of survey methods for measuring cat abundances that use trail cameras versus walking transects.

Aspect	Trail camera	Walking transect surveys
Expenses	Equipment: Camera, memory card and battery costs; cameras can be stolen/break and need to be replaced. Field technician salary	Equipment: Clipboards, rangefinder(s); Surveyor(s) salary.
Time to conduct study	Deployments can spread weeks–years.	Replicate surveys need to take place close together in time. Additional surveys and replicates are needed for longer term/seasonal estimates
Time to process data	Long: need to sort through thousands of pictures per camera.	Short: input data per transect.
Investigator experience	Minimal training required. May be possible to involve citizen scientists or landowners.	Trained surveyor needed.
Study species	Any species; useful for elusive, skittish, or nocturnal species.	Best for abundant and diurnal species.
Permission/Permits	Permission required to set up cameras: can result in difficulties placing cameras on public, commercial and industrial land.	No permission needed to use public streets. Permission needed if access to private land is required. Difficulty in accessing areas away from streets.
Study Aims	Counting and tracking individuals' movements, identifying species habitat associations, inter/intra-species interactions, abundance/occupancy.	Counting individuals, identifying species habitat associations, abundance/occupancy.

Part 5: Examples of trail camera footage

Figure S1. Example of how a cat with an orange coat can appear to be two separate cats when viewing night (infrared) and day images. In these cases, identifying features such as the tail and body markings, body size and shape were used to determine this was the same cat.

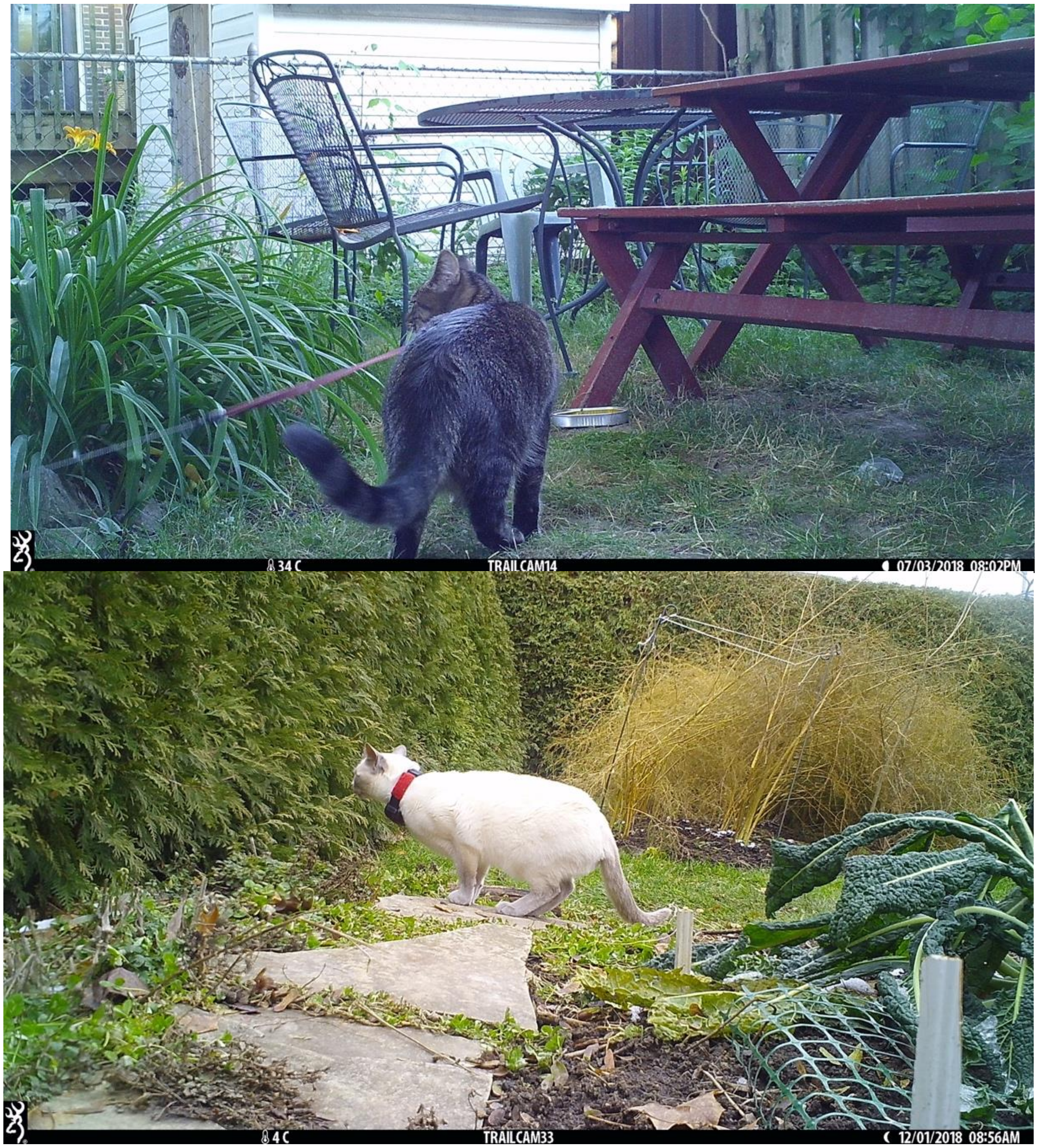

Figure S2. Example of two different cats photographed using trail cameras in Wellington County, ON, Canada that were removed from the study because they were not designated as free-roaming due to physical restraints (above: leash, below: e-fence).

Figure S3. Example of the same cat photographed using trail cameras in Wellington County, ON, Canada, during different parts of annual period. The distinct coat pattern allowed us to easily determine this was the same cat. Pictures taken on June 27th, 2018 (top), November 8th, 2018 (middle), and February 20th, 2019 (bottom).

Figure S4. Examples of different cats photographed using trail cameras at the same camera site in Wellington County, ON, Canada. Pictures taken in August 2018.

Part 6: Covariates used to estimate local cat abundance

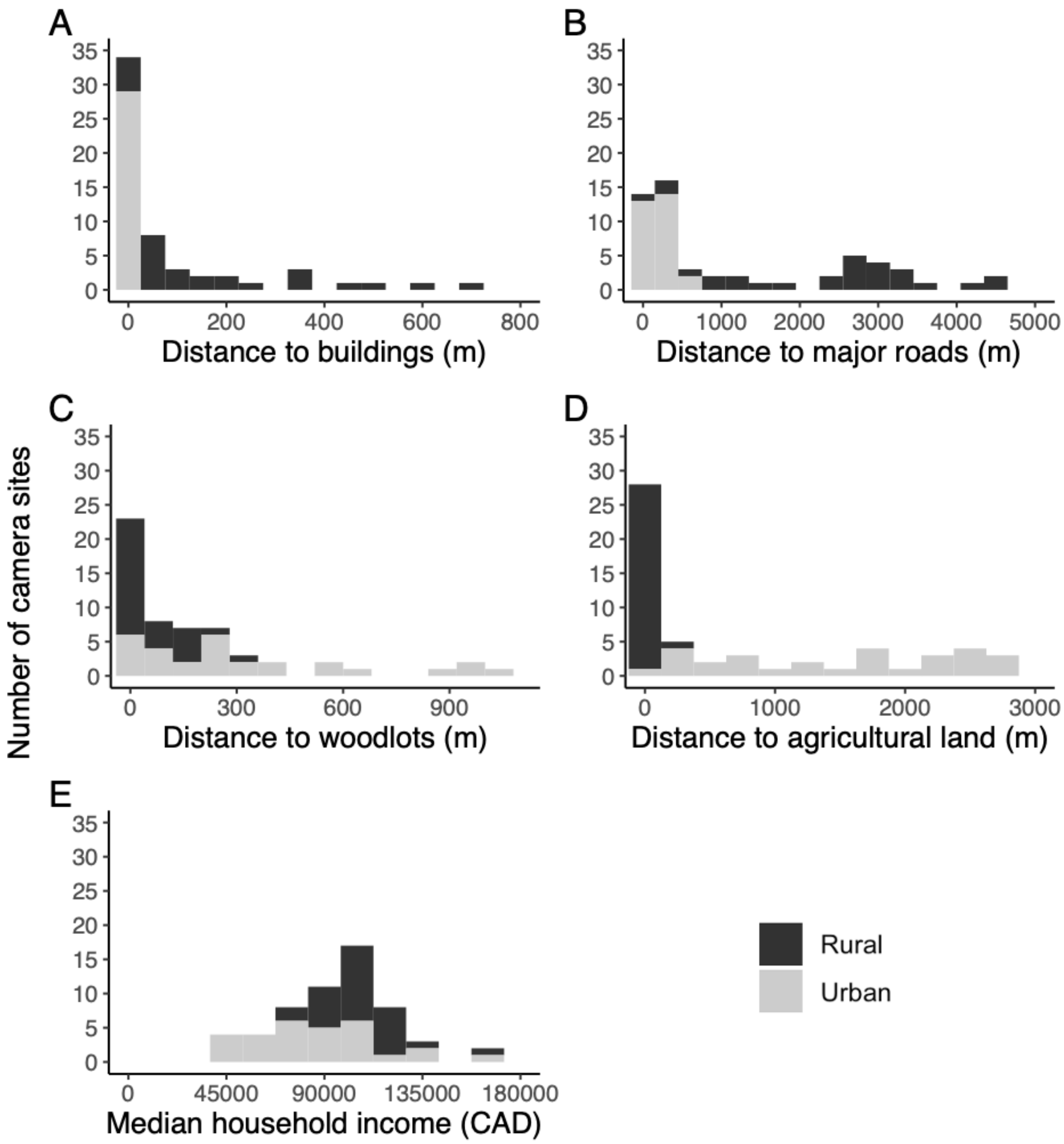

Figure S5. The corresponding number of camera sites in relation to habitat features that may influence local cat abundance in Wellington county, ON, Canada. Characteristics: distance to buildings (m; A), major roads (m; B), woodlots (m; C), agricultural land (m; D), and median household income (CAD; E).

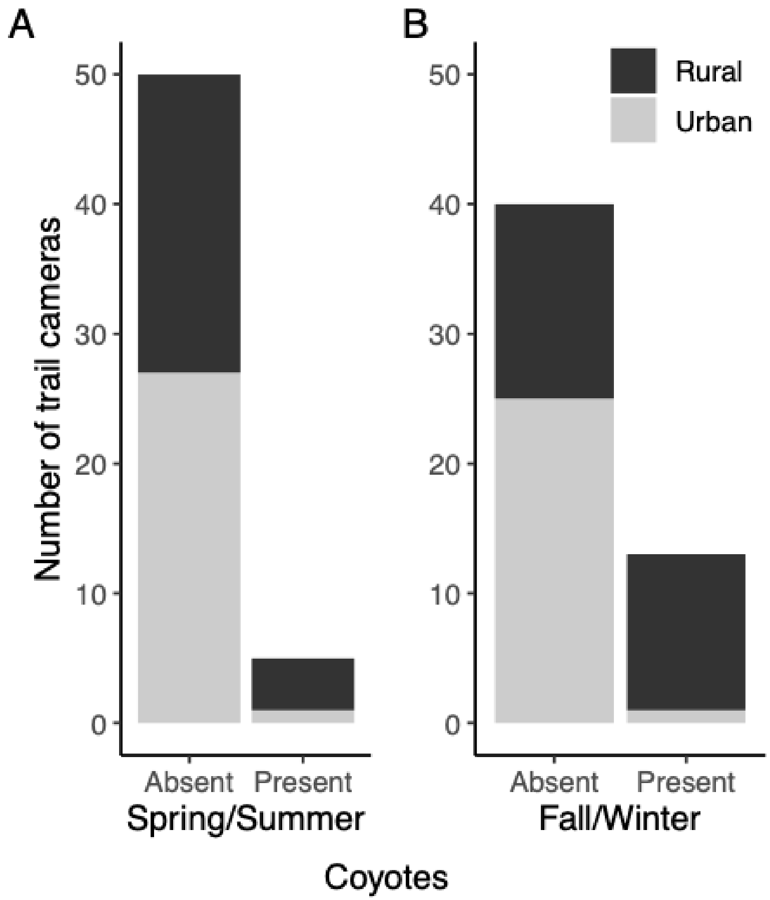

Figure S6. The number of camera sites where coyotes were sighted in the (A) spring/summer and (B) fall/winter within the Wellington county, ON, Canada study site. The presence of coyotes at a site was determined from trail camera images. Coyotes were absent across most sites in both periods of the year, however almost twice as many coyotes were present in the fall/winter compared to the spring/summer.