Fawn bedsite selection by a large ungulate living in a peri-urban area

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Abstract

Human populations continue to grow at an unprecedented rate, along with the associated anthropogenic footprint on wildlife habitats. As a result, human-wildlife conflict in expanding peri-urban and urban areas is of increasing concern. Empirical data from wildlife research carried out within human dominated landscapes are key to understanding the effects of human pressures on wildlife ecology and behaviour, exploring wildlife behavioural flexibility (or phenotypic plasticity), and informing wildlife management decisions. Here, we explored how female fallow deer (*Dama dama*) and their fawns responded to human and dog presence during the birthing period in the largest walled urban park in Europe, which receives 10 million visitors along with their dogs every year. We collected data on 481 bedsites utilised by 285 neonate fawns across three consecutive fawning seasons, gathered fine-scale data on humans (and dogs) space use, and built Resource Selection Functions at multiple spatial scales. We found that, when choosing bedsites to give birth and leave fawns unattended, fallow deer mothers significantly avoided hotspots of park visitors on foot (and their dogs) along the hiking trail network, maintaining a distance of at least ~200m. Bedsites were also unlikely to be in close proximity, within 50 meters, of paved roads used by vehicle traffic. Additionally, fallow deer mothers were found to select for dense understory vegetation for bedsites, providing low visibility to conceal their offspring. Our results provide detailed insights into how female fallow deer adapt their spatial and habitat selection for bedsites during the fawning season in response to human activities, and provide clear indications to wildlife managers to preserve traditional fawning sites in order to alleviate human-wildlife conflict during a critical period of the deer annual biological cycle.

Keywords: Human-wildlife conflict, deer, Urban wildlife, Resource Selection Functions, bedsite selection.

Introduction

We are currently in the Anthropocene, defined by extensive human impact on our planet's ecology and geology (Morelli et al., 2020). It is estimated that more than 50% of human populations will be concentrated in cities by 2030 (Lowry et al., 2013, Shochat et al., 2006), with these cities presently expanding at an unprecedented rate worldwide (Wolff et al., 2018). This is associated with synurbanisation, i.e. wildlife increasingly living in and adapting to urban environments, with a concurrent increase in encounters between humans and wildlife (Barber et al., 2010, Gallo et al., 2019, Huijbers et al., 2013, Tucker et al., 2018). Several concerns have been raised about the potential for artificial selection processes to occur as a result of human-wildlife interactions within urban settings (Griffin et al., 2022, Lowry et al., 2013).

Empirical research has repeatedly shown that human presence can affect wildlife behaviour significantly (Gander and Ingold, 1997, Hebblewhite et al., 2005, Recarte et al., 1998, Shen-Jin et al., 2007, Whittington et al., 2004). Wildlife species may increase flight response and avoidance behaviours in locations with high human presence (Recarte et al., 1998), as well as alter their habitat use and movement (Gander and Ingold, 1997, Hebblewhite et al., 2005, Recarte et al., 1998, Shen-Jin et al., 2007, Whittington et al., 2004). Within human-dense urban settings, however, wildlife species need to adapt their anti-predator strategies (e.g. reduced flight distance) as fleeing any time that they encounter humans would be energetically expensive. This highlights how behavioural flexibility (or phenotypic plasticity) may be an important characteristic for succeeding in urban environments (Lowry et al., 2013).

Within urban settings, humans are more likely to use green areas and urban parks when walking their dogs, with a higher probability of encountering urban wildlife in these areas. Dog presence has been shown to alter wildlife behaviour, though responses vary depending on the wildlife species [14-16]. Canine presence increases alert and escape distances in many ungulate species, and has been associated with a reduction in offspring:female ratios (Manor and Saltz, 2004, Martinetto and Cugnasse, 2001, Miller et al., 2001). These decreases in offspring production could be caused by associated increases in vigilance in mothers, decreased breeding

behaviour, or a combination of both (St. Clair and Forrest, 2009). Due to the importance of successful breeding seasons in keeping wild animal populations healthy, changes in breeding behaviours during this sensitive period can create a knock-on effect, with potential long-term consequences for the composition (i.e., age ratios) of wild populations and natural selection processes (Lowry et al., 2013). As humans and their dogs are both predicted to come into more regular contact with wild animals within increasingly human dominated environments, studies assessing the dual consequences of human and canine presence on wildlife are increasingly important.

In ungulates, offspring and their mothers exhibit various strategies to increase their chances of offspring survival during their first weeks of life; this constitutes a continuum ranging from "hider" to "follower" species (Walther, 1961a). As a "hider" species, fallow deer (*Dama dama*) mothers hide their offspring in dense vegetation, where they remain separated for several hours at a time (Chapman and Chapman, 1997). Selection of these "bedsites" after parturition plays a major role in increasing offspring survival (Gerlach and Vaughan, 1991, Tull et al., 2001, Van Moorter et al., 2009, Monestier et al., 2015). During this vulnerable time for offspring, fallow deer mothers decrease their home-range sizes and select for denser habitats to increase concealment and decrease predators' ability to detect fawns (Ciuti et al., 2006). However, research to date has focused almost exclusively on rural and isolated environments, with little understanding of bedsite selection in peri-urban landscapes. (Smith and Lecount, 1979, Long et al., 1998, Piccolo et al., 2010). This highlights the need for further research aimed at providing data that would stir management of wildlife populations within urban settings.

Here, we have gathered unique data on 481 bedsites used by 285 individual fallow deer fawns across 3 consecutive fawning seasons in the largest walled urban park in Europe, the Phoenix Park, located at the heart of Dublin, Ireland. Our goal was to explore bedsite selection by fallow deer mothers that have adapted to live in a peri-urban area under high human pressure. Phoenix Park is an ideal model for this study as it receives 10 million annual visitors, typically on foot with many walking their dogs, and large amounts of vehicular traffic (which includes commuters to and from Dublin city centre) in a relatively small green area at the edge of a capital

city. This is the largest dataset ever compiled on bedsite selection in a large ungulate with fine scale data on human and dog proximity in an urban parkland.

We made 3 main predictions for how females may adapt to peri-urban settings during the fawning season. We also aimed to estimate threshold distances (distance to roads and hiking trails) and vegetation characteristics (vegetation density and related visibility) that may be critical for park managers to create buffer zones and strict protected core areas for wild deer during this important stage of their annual biological cycle. Our main 3 predictions were: (i) fallow deer mothers are predicted to select bedsites characterized by denser vegetation and lower visibility, when compared to random available sites, in order to reduce fawn detectability by terrestrial predators (including humans); (ii) bedsites are predicted to be located outside and at greater distances from hotspots of human presence (which also represent dog presence) along hiking trails; and (iii) mothers are predicted to avoid roads with vehicle traffic. Despite being the largest urban park in Europe (~ 7km^2), most of the park's space is dominated by park visitors during the day; as a consequence, fallow deer mothers are expected to find the best balance between selecting suitable vegetation and an appropriate distance from humans for their fawns' bedsites, giving us the opportunity to describe deer plasticity and adaptation to extreme conditions in terms of human presence.

Materials and methods

Study site

The study was conducted in Phoenix Park, a 709ha urban park located in Dublin, Ireland (53°22'N, -6°21'W, Fig. 1), which receives an estimated 10 million visitors annually (Office of Public Works, OPW, official data). The habitats are mainly grassland (56%) and woodland (31%), with 7% of the park covered by roads and buildings (OPW, 2020). The Park management (OPW) maintains a fallow deer population of around 600 individuals (end of summer population estimate, which includes newborn fawns, OPW official data), and this number is kept constant by yearly culls. The only natural predator in the park is the red fox, which seldomly predates newborn fawns, although unleashed dogs have been documented chasing fawns.

Data collection

Fawn captures and bedsite characteristics

Fawns have routinely been captured in June and ear-tagged with unique numbered plastic tags (Allflex medium; Mullinahone Co-op, Ireland) since the early 1970s as part of the monitoring and management of the fallow deer herd (Hayden et al., 1992, Amin et al., 2021). We split the geographical area typically used by females as fawning sites (displayed in both Fig 1 and Fig. 2a) into seven sectors. These were patrolled routinely, visiting 2-3 sectors daily, with each sector visited at least once every 2-3 days. Approximately 10-15 trained capture team members supervised by a certified wildlife biologist captured fawns using circular fishing nets (1–1.5m of diameter) manoeuvred by long handles (1.5m long). The capture team usually worked between 9:00 to 16:00 hrs daily, 7 days a week for more than three consecutive weeks, with the goal of tagging the majority of the newborn fawns within this population (~85%).

The field crew collected data on fawns and their associated bedsites following a well-defined protocol (see Amin et al. (2021) for a full description of the information collected on fawns). For this study, we used the following data: fawn identity (ear tag code) and sex; fawn weight (i.e. an objective proxy for age *sensu* Amin et al. (2021), determined by placing the fawn into a 100-litre bag, which was weighed using a digital scale (resolution: 0.01 kg—Dario Markenartikelvertrieb)); GPS coordinates of the bedsite (Garmin etrex 30 hand-held unit); and bedsite visibility (see below for full description). Fawns were routinely recaptured to monitor body growth (Griffin et al., 2023), therefore allowing us to collect bedsite characteristics in older fawns. Our final database consisted of fawn capture data collected in 2018 (n = 102 individual fawns), 2019 (n = 83), and 2020 (n = 100 individuals captured). Because of recaptures, we gathered data on a total of 481 bedsites (n = 163 in 2018, n = 155 in 2019, and n = 163 in 2020, Fig. 3).

We assessed the average visibility of the fawn bedsite (*sensu* Bongi et al., 2008) as follows: from a distance of 10 m along the four cardinal directions we recorded the proportion

of visually unobstructed triangles on a cardboard shape the size of a standing fawn (height: 45 cm, width: 36 cm), which was placed at the location that the fawn was found. We observed the cardboard shape from an eye height of 70 cm, which approximately corresponds to the eye height of a red fox. The study protocol and all research procedures were approved by the UCD Animal Research Ethics Committee for the duration of 5 years (2018–2023), under the permit AREC-E-18-28.

Presence-available study design

We used a presence-availability design to depict bedsite selection using Resource Selection Functions (RSFs) (Thurfjell et al., 2014, Ciuti et al., 2018). RSFs allowed us to estimate the relative probability of selection by comparing environmental features of used sites (the sites where fawns were found and captured) to those of sites selected at random (random available points). Random available points were selected in R 3.6.3 (Team, 2020) within the capture areas with the rule that they each had to be at least 20m apart to avoid the overlap (and therefore dependency) of the visibility measurements taken at each bedsite. Random points were visited during the fawning season and, for each location, we recorded the visibility following the same protocol adopted for the true fawn bedsites (Fig. 3).

Spatially-explicit data collection on park visitors and their dogs during the fawning season

We collected data on park visitors and their dogs during the fawning season of 2019 (7th-28th of June, Fig. 2b) with the goal to build a spatially-explicit model of human presence. Hiking trails were the same in 2018, 2019, 2020, and our goal was not to estimate the variation in human presence across years, but rather understand which hiking trails were commonly used by park visitors to create a spatially-explicit map of fear. We walked at a constant pace (5km/hr) along all hiking trails following a strict systematic stratification so as to survey each trail equally as a function of time of the day and day of the week. We used a GPS handheld unit to record the position of human and dog presence on paths or trails. If people or dogs were outside the path or trail (quite rare, see Fig. 2b), their GPS location was accurately estimated by combining data from the GPS hand-held unit (Garmin etrex 30), a rangefinder (Hawke Endurance), and a compass (Silva). For each observation, we counted the number of visitors and dogs.

Study Site

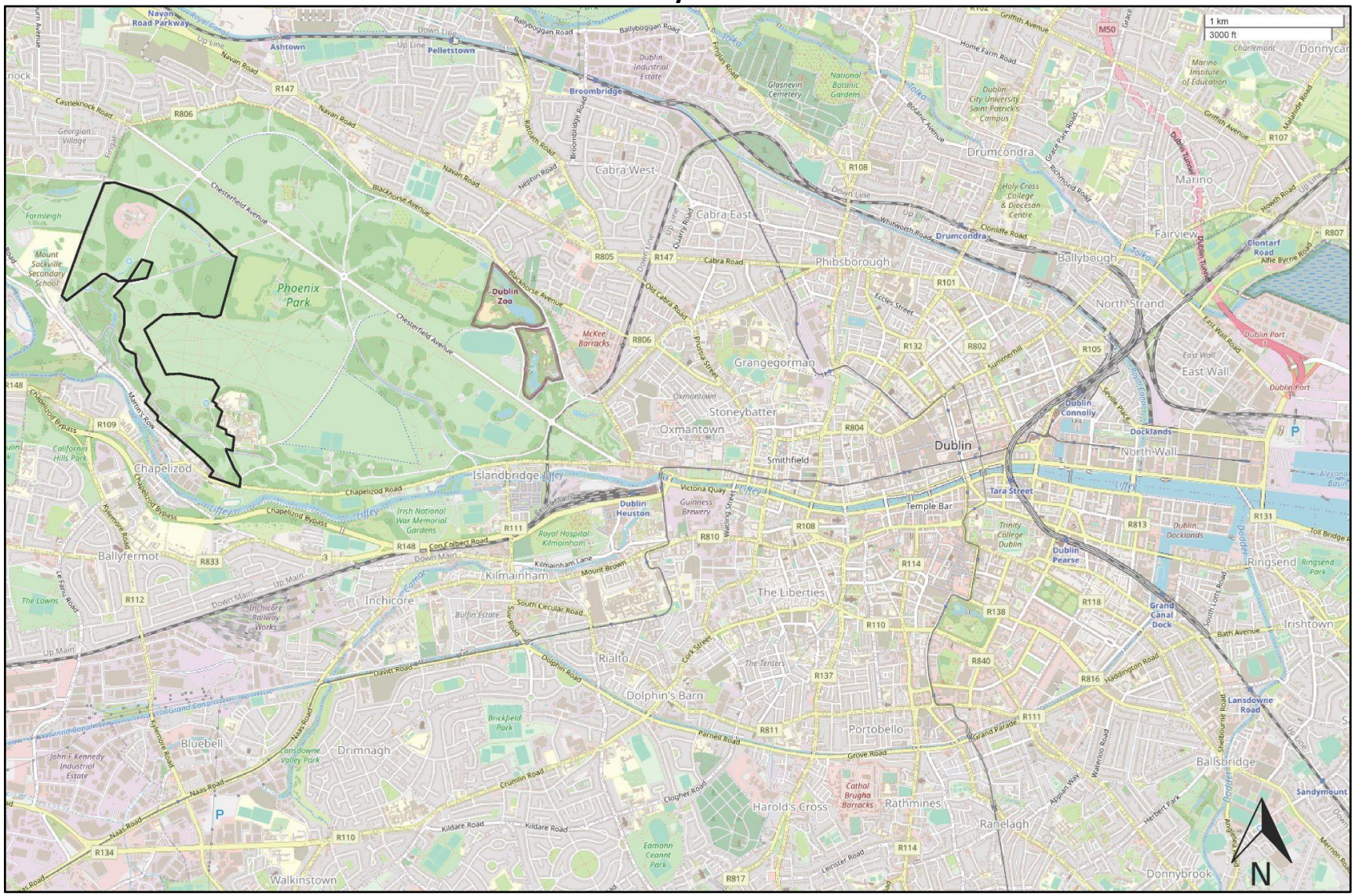

Fig. 1: Map of the Dublin metropolitan area, with the study site location, the Phoenix Park, clearly visible as the largest green space in the top left of the map. The highlighted polygon (in black) in the western side of Phoenix Park represents the fallow deer fawning area.

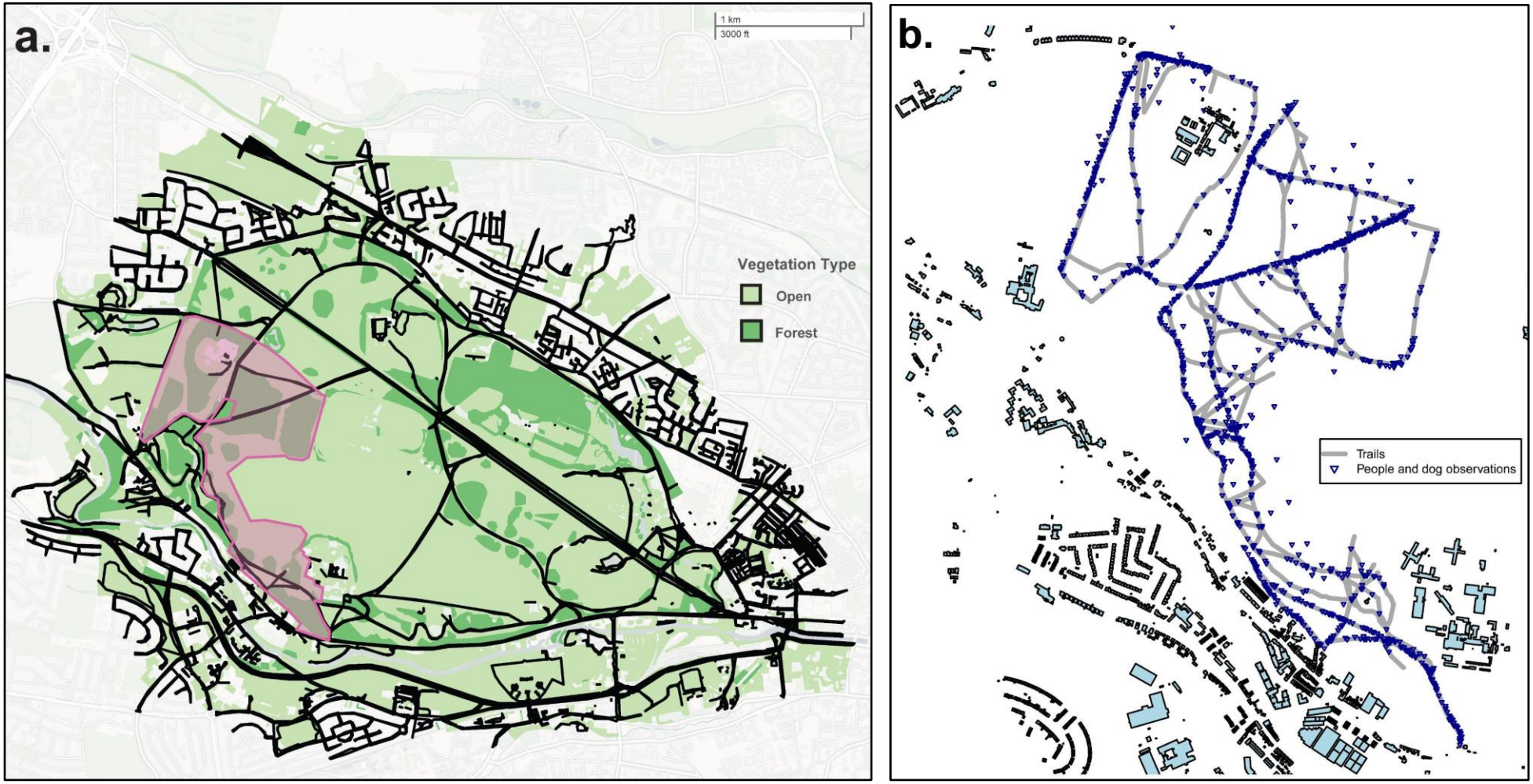

Fig. 2: Map of the Phoenix Park, Dublin (a) including habitats (open, forest), roads (black linear features), and the traditional fallow deer fawning area (pink polygon) which has been patrolled by the team during ear-tagging procedures. Within the fawning area (b), hiking trails (grey lines) were systematically walked during the fawning season to locate park visitors and their dogs (blue triangles).

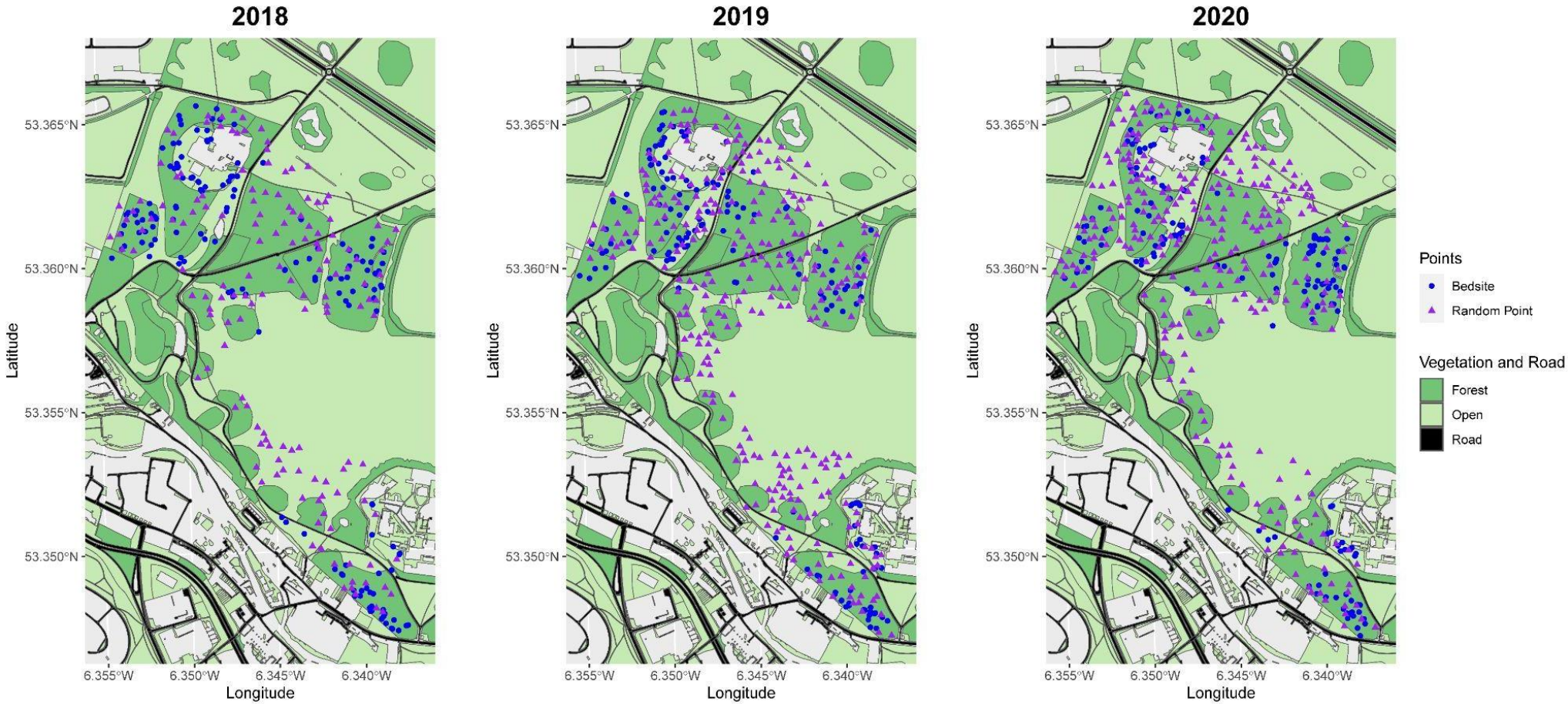

Fig. 3: Locations of fallow deer fawn bedsites (blue circle) and random available points (purple triangle) across the 3 years of the study (2018-2020) within the traditional fawning area (i.e., pink area in Fig. 2a) of the Phoenix Park, Dublin.

Data Analysis

In the following sections we described our analyses step-by-step. First, we modelled the human and dog observations using generalized additive models (Wood, 2017) to generate a spatially-explicit raster, i.e. a "risk map" of human-dog activity. Second, we computed the distance from paved roads for both bedsites and random available points. We also extracted the vegetation type using the land use map of the park (Ordnance Survey of Ireland, official data), as well as the information from the human and dog "risk map". In order to assess bedsite selection at different spatial scales, we generated buffers of different sizes around each bedsite (i.e., 250m, 375m, 500m, 750m, 1000m, 1500m and 2500m) and generated multiple databases where bedsites' characteristics were compared to those of random available points within increasing distances (i.e. availability computed at the individual level), therefore adopting a resource selection design III *sensu* Manly et al. (2007). After screening for the collinearity of model predictors, we built multiple resource selection functions, corresponding to different spatial scales. All analyses were carried out in R 3.6.3 (Team, 2020).

More in detail, we started by creating the heat map for park visitors and dogs in the fawning area using the human and dog presence observations. Firstly, we created a grid of 50x50m cells on top of the fawning area. The grid was used to separately count the number of humans and dogs in each cell during weekdays and the weekend. Since the observations of dogs were considerably lower than the observations of humans, dog presence was converted into a binomial value (presence-absence). We then fitted two spatial Generalized Additive Models (GAMs) for humans and dogs as a function of the fawning area location (east coordinate, north coordinate) and day of the week, specified in R as follows:

Human presence model: gam(human presence ~ s(east coordinate, north coordinate, k=29) + day of the week, data = dataframe, family = quasipoisson).

Dog presence model: gam(dog presence ~ s(east coordinate, north coordinate, k=29) + day of the week, data = dataframe, family = binomial).

We opted for a quasipoisson correction for the human presence model to account for a mild overdispersion (Zuur et al., 2009). For both models, the spline knots were manually set to 29 to avoid overfitting the data following the indications from the *gam.check* function (Wood, 2017). Both models were used to predict the human presence (number of visitors) and probability of dog presence at the 50 x 50 m resolution using the *predict* function in *mgcv* (Wood, 2017).

We extracted environmental data for both used and available points, namely vegetation type using the o*ver* function from the *sp* package (2 levels: forest, and open habitat corresponding to grassland), predicted number of visitors and likelihood of dog presence, and distance to the nearest paved road (where vehicular traffic was allowed, in meters) using the function *gDistance* from the *sp* package (Pebesma and Bivand, 2005, Bivand et al., 2013). As briefly mentioned earlier, we created buffers of 250m, 375m, 500m, 750m, 1000m, 1500m and 2500m around all bedsites. The smallest size diameter was chosen since it was the smallest buffer that allowed for all bedsites to be compared with enough random available points at such a small scale. The largest scale corresponded to the longest diameter of the fawning area, therefore in this instance availability was defined at the population level. Intermediate buffers were included to describe how resource selection varies across scales. Buffer zones were created using the *gBuffer* function from the *sp* package in R.

We screened all variables described above for a collinearity (Dormann et al., 2013), and found that the spatially-explicit predictions of number of park visitors were highly collinear with the likelihood of dog presence (Supplementary Table S1). We therefore retained the number of park visitors since it was count data and able to give a better picture of different levels of disturbances when compared to the binomial likelihood of dog presence.

Resource Selection Functions built assuming an exponential form require normally distributed continuous predictors (Thurfjell et al., 2014). Therefore, prior to starting our modelling stage, we transformed both the human presence and road distance data to meet model assumptions. We succeeded with the normalisation of the human presence, which was achieved using a box cox transformation, a family of power transformations which selects the best mathematical function for the data transformation to achieve data normality. The selection is achieved using a log-likelihood procedure to find lambda and transform the non-normally

distributed variable (see Supplementary Fig. S1 and S2) using the *MASS* package [37]. We were not able to improve the distribution of road distance; this variable was therefore converted into a two-level categorical predictor (close vs far) using a threshold point of 50 m. The threshold point was selected by running a sensitivity analysis with preliminary resource selection functions fitted with different threshold values, and the best model was the one with the lowest Akaike Information Criterion, AIC (Supplementary Fig. S3).

In order to estimate the parameters for the multi-scale RSFs, we fitted Generalized Mixed-effect Models (GLMM, *glmer* function from package *lme4* (Bates et al., 2015)) with a binomial distribution of errors (response variable: used points, 1s; and random available points, 0s) and fawn identity as random intercept. We used the same model structure across the different spatial scales ranging from 250m to 2500m (Table 1). We scaled numerical predictors to improve model convergence and included quadratic terms to account for non-linear effects. Parameters estimated by the GLMM were extracted and plugged into the RSF taking the exponential form (Thurfjell et al., 2014, Fechter et al., 2019, Brivio et al., 2019).

Table 1: Structure of the GLMM models fitted to estimate the parameters for the Resource Selection Functions at different spatial scales (ranging from 250 to 2500 meters).

GLMM Model structure (binomial distribution of errors)			
Response Variable	Random Effect	Explanatory Variables	
Used/available (1,0)	Tag (identification code of the fawn)	Bedsite visibility (ranging from 0 to 1)	Year (2018, 2019, 2020)
		Road distance (lower or equal to 50 m, greater than 50 m)	Sex of fawn (male, female)
		Human presence (predicted number per 50x50m pixel)	Fawn weight (in kg)
			Habitat (forest, open)

Note that RSFs estimate relative probabilities of selection (Thurfjell et al., 2014). Using RSF equations at multiple spatial scales, we built a number of scenarios to depict bedsite selection as

a function of the predictors that we have hypothesized to drive this ecological process: road distance, human presence (collinear with dog presence), and visibility of the bedsite.

Results

We depicted human abundance and dog encounter likelihood maps (50 x 50 m resolution) of the fawning area in Phoenix Park as predicted by the Generalized Additive Models in Fig. 4. Details on the two GAMs can be found in the Supplementary Table S2. We reported the parameter estimates of the 7 GLMMs (fitted across the 7 spatial scales ranging from 250m to 2500m) in Table 2 (displaying the key predictors bedsite visibility, human presence, and distance to paved roads) and Supplementary Table S3 (displaying the other confounding variables included in the models).

For the GLMM models across the varying spatial scales, we found human presence was always inversely related to the relative probability of selection, indicating avoidance of human hotspots (Table 2, Fig. 4). In terms of statistical significance, this was particularly remarkable at the larger spatial scales (Fig. 5), showing that used bedsites were located at greater distances from the hotspots of human presence compared to random available points. This, however, was not true at the smallest spatial scale (250 m, Fig. 5), indicating that the choice of a bedsite at the smallest spatial scale (compared to the characteristics of the closeby random available points) was no longer affected by human presence because both bedsites and random points were far from human hotspots. A radius of 187.5m for the 375m buffer was the minimum distance where the avoidance of human hotspots was flagged as significant (Table 2, Fig. 5).

We found bedsite visibility to be a key driver of selection, with bedsites characterised by significantly lower visibility (denser vegetation) than random available points at all spatial scales (Table 2). Finally, distance to roads was positively related to the relative probability of selection, with bedsites always located at distance greater than 50m from roads with vehicle traffic. We depicted the key scenarios which describe bedsite visibility and avoidance of human hotspots and roads in Fig. 6 and Fig. 7 which can be used by wildlife managers to protect key fawning areas. This includes details on the actual number of people affecting bedsite selection.

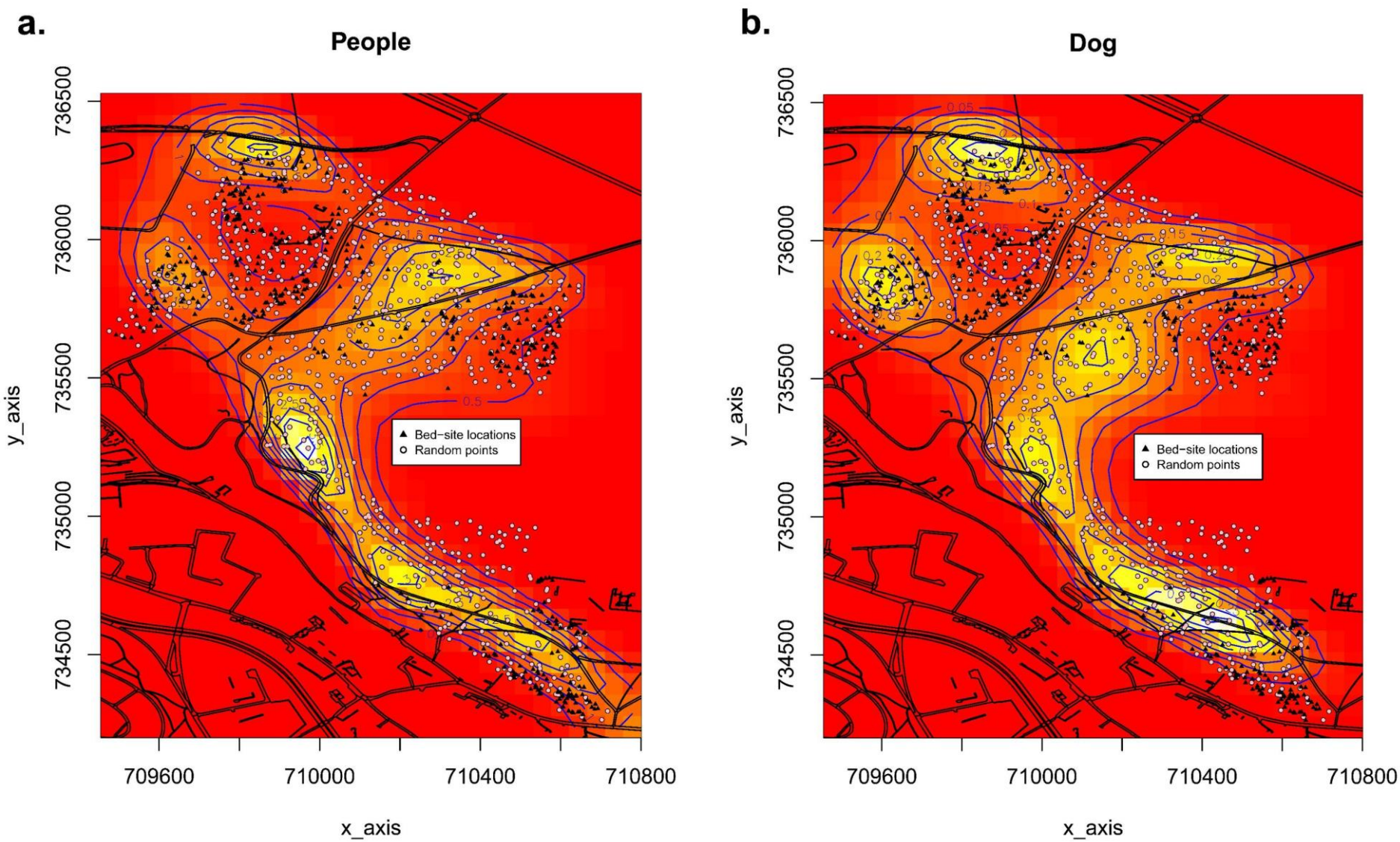

Fig. 4: Predicted maps depicting human abundance (a: greater abundance indicated by lighter colours) and likelihood of dog encounter (b: greater likelihood indicated by lighter colours) in the fawning area of Phoenix Park. Both maps include bedsite locations (triangle) and random available points (circle). X-axis (corresponding to longitude) and Y-axis (corresponding to latitude) are expressed in meters. Note how the location of the fawn bedsites are outside the hotspots of people and dog occurrence.

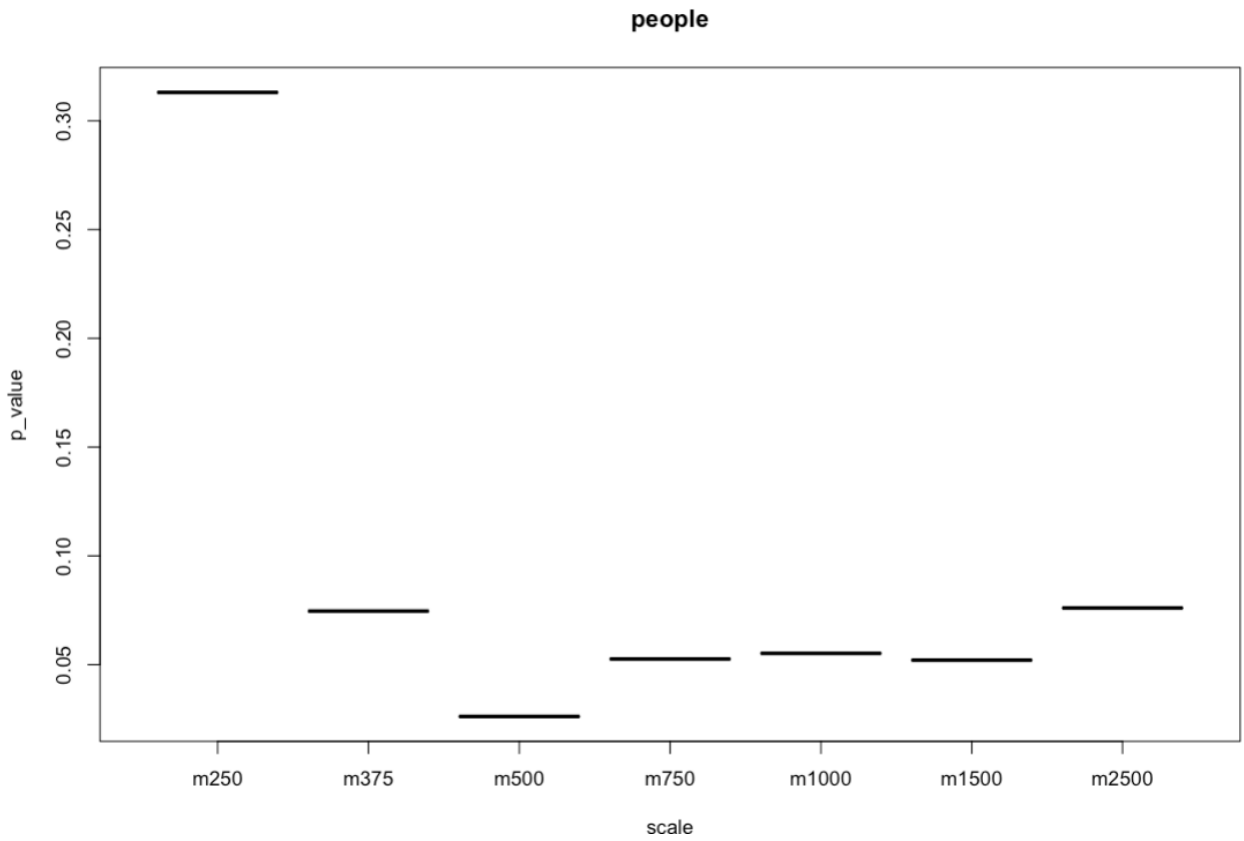

Fig. 5: Significance (y-axis) of the human presence predictor as estimated by the GLMMs across spatial scales (x-axis). Mother fallow deer strongly avoided hotspot of human presence at larger spatial scales (from 500m from the bedsite onward), therefore not affecting the choice of the bedsite at the smallest spatial scale (i.e., 250 meters) where both bedsites and random available points were far from human presence hotspots in the park.

Table 2: Parameters estimated by the GLMMs fitted across 7 spatial scales and explaining the relative probability of bedsite selection by fallow deer in the Phoenix Park, Dublin. Only key predictors (bedsite visibility, road distance, and human presence) are included in this Table, whereas the other predictors can be found in the Suppl. Table S3. Significance abbreviations: *** p<0.001, ** p<0.01, * p<0.05, · p<0.1, ns p>0.1

Scale	Variables	Estimate	Std. Error	Z value	Pr(>|z|)	Significance
250m	Visibility	-2.30137	0.21582	-10.663	<2e-16	***
	Visibility^2	1.29053	0.25683	5.025	5.04e-07	***
	Road distance [>50]	0.30066	0.12802	2.349	0.0188	*
	Human presence	-0.05440	0.05392	-1.009	0.3130	ns
	Human presence^2	-0.01307	0.05243	-0.249	0.8031	ns
375m	Visibility	-2.44699	0.22051	-11.097	<2e-16	***
	Visibility^2	1.38380	0.26738	5.175	2.27e-07	***
	Road distance [>50]	0.39127	0.12556	3.116	0.00183	**
	Human presence	-0.09753	0.05470	-1.783	0.07462	.
	Human presence^2	-0.08767	-0.05595	-1.567	0.11710	ns
500m	Visibility	-2.54987	0.22222	-11.475	<2e-16	***
	Visibility^2	1.45634	0.27211	5.352	8.69e-08	***
	Road distance [>50]	0.39796	0.12392	3.212	0.00132	**
	Human presence	-0.13049	0.05869	-2.223	0.02619	*
	Human presence^2	-0.19872	0.06814	-2.916	0.00354	**
750m	Visibility	-2.55866	0.22764	-11.240	<2e-16	***
	Visibility^2	1.43488	0.28440	5.045	4.53e-07	***
	Road distance [>50]	0.37582	0.12166	3.089	0.002008	**
	Human presence	-0.11985	0.06183	-1.938	0.052575	.
	Human presence^2	-0.26803	0.07587	-3.533	0.000411	***
1000m	Visibility	-2.45717	0.22983	-10.691	<2e-16	***
	Visibility^2	1.33290	0.28778	4.632	3.63e-06	***
	Road distance [>50]	0.20170	0.12123	1.664	0.09616	.
	Human presence	-0.11980	0.06248	-1.917	0.05519	.
	Human presence^2	-0.29164	0.07787	-3.745	0.00018	***
1500m	Visibility	-2.41233	0.22980	-10.497	<2e-16	***
	Visibility^2	1.30659	0.28643	4.562	5.08e-06	***
	Road distance [>50]	0.20452	0.12151	1.683	0.0923	.
	Human presence	-0.12457	0.06413	-1.943	0.0521	.
	Human presence^2	-0.35520	0.07985	-4.448	8.65e-06	***
2500m	Visibility	-2.37996	0.22760	-10.457	<2e-16	***
	Visibility^2	1.29965	0.28195	4.610	4.04e-06	***
	Road distance [>50]	0.26029	0.12131	2.146	0.0319	*
	Human presence	-0.11213	0.06320	-1.774	0.0760	.
	Human presence^2	-0.32845	0.07786	-4.219	2.46e-05	***

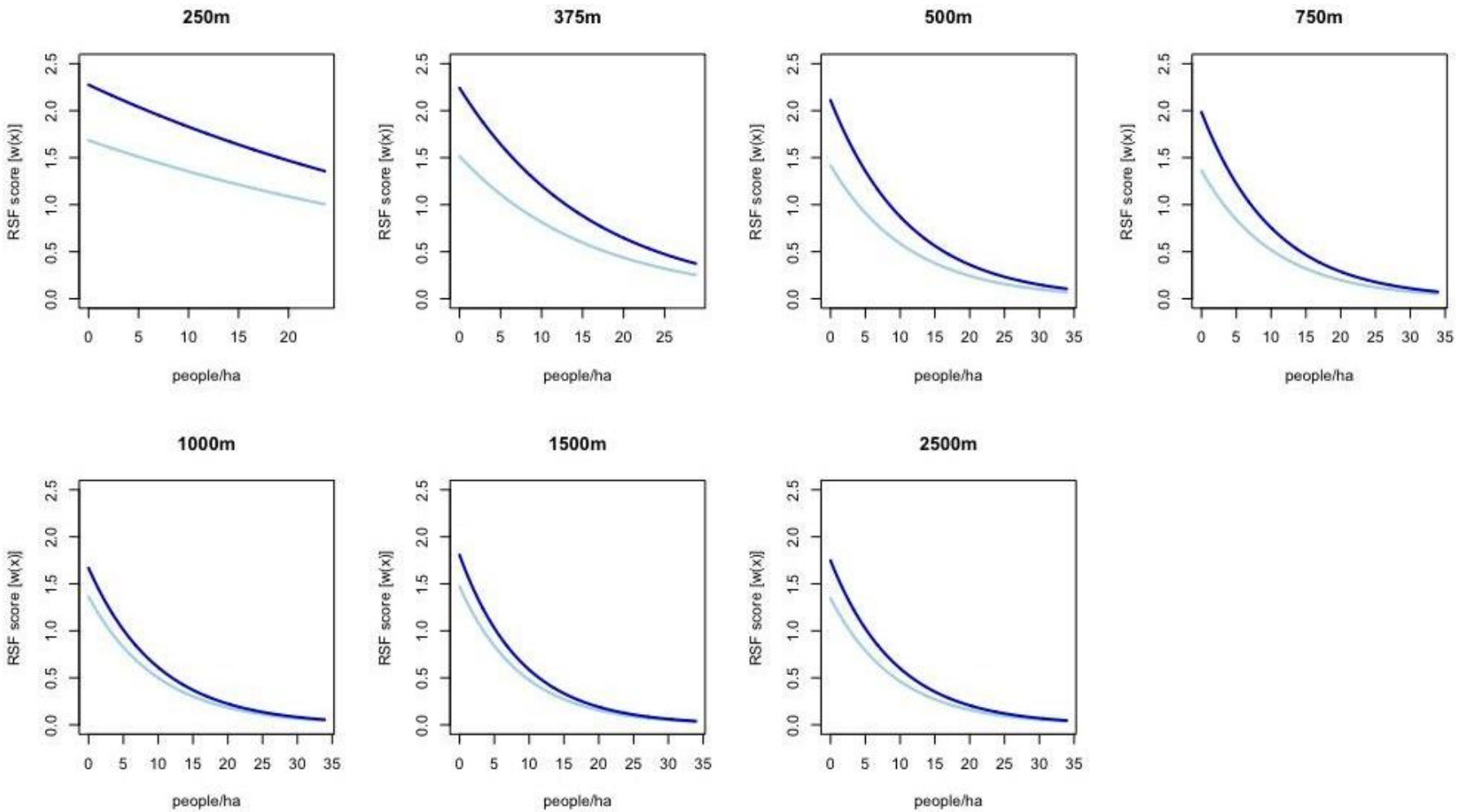

Fig. 6: Predicted effect of the number of people per hectare (x-axis, 100 x 100 m) on the relative probability of bedsite selection (y-axis, RSF score [w(x)]) when the distance to the closest road is between 0 and 50 meters from the road (light blue line) or greater than 50 meters from the road (dark blue line). Note the stronger selection for bedsites far from roads, particularly when the number of people per hectare is lower. Also note avoidance of humans was remarkable at the larger spatial scales (e.g. 1500m, 2500m), and weaker at the smallest spatial scales, where both bedsites and random available points are both far from the hotspots of human presence.

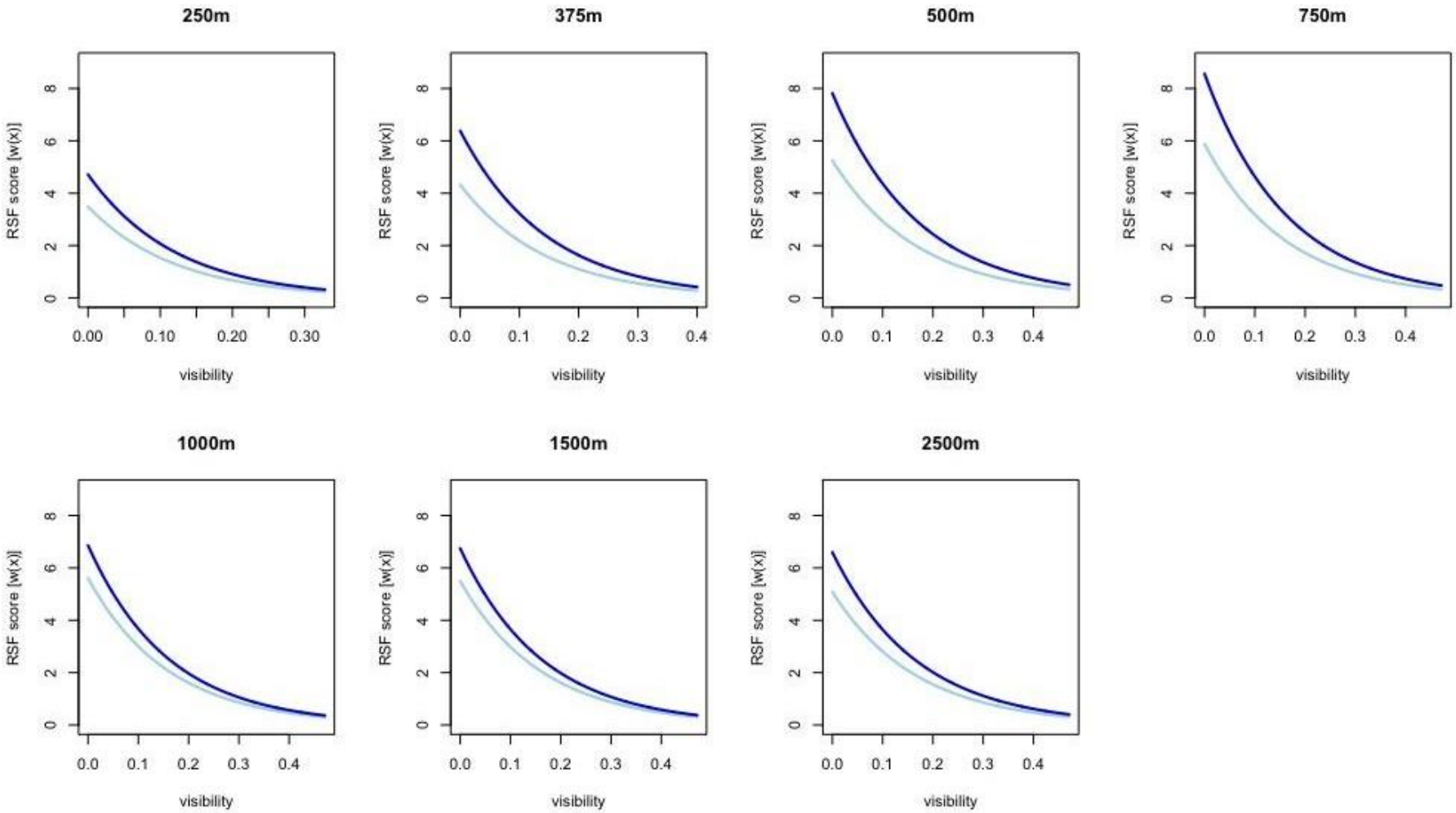

Fig. 7: Predicted effect of the bedside visibility (x-axis, ranging from 0% to 50% of a standing fawn visible from 10 meters and eye height of 70cm) on the relative probability of bedsite selection (y-axis, RSF score [w(x)]) when the distance to the closest road is between 0 and 50 meters from the road (light blue line) or greater than 50 meters from the road (dark blue line). Note the stronger selection for bedsites with low visibility and more distant from roads when compared to random available points at all spatial scales.

Discussion

We found that, when choosing bedsites to give birth and leave fawns unattended, fallow deer mothers significantly avoided hotspots of humans on foot (which is also associated with dog presence) along the hiking trail network, keeping a distance of at least 187.5 m from them. As for dog presence, it was not included in the analysis since it resulted collinear to human presence. However, human presence is also a proxy for dog presence since it accounts for the overall predator presence in the eyes of the fallow deer mothers (i.e. dogs would always accompany their owners). In addition, bedsites were located away from paved roads used by vehicular traffic (rarely being located within 50 meters from a road) and were characterized by dense understory vegetation with low visibility. For the first time, through the combination of bedsite data and observations of human and dog presence, we described bedsite selection at a resolution never attempted before, gathering empirical evidence on the features of bedsites selected by mothers to successfully give birth and protect their fawns during their first weeks of life in a peri-urban setting. This data can be used by urban wildlife managers to protect fawning sites and alleviate human-wildlife conflict during this critical period of the deer annual biological cycle. This is fundamental for maintaining high welfare standards for urban wildlife through the implementation of good management practices.

Despite both humans on foot and vehicular traffic being highly predictable in the park, our study showed higher disturbance from human presence on foot compared to roads used by vehicular traffic. This may be because vehicles on the road follow a strictly predictable course (vehicles are not allowed off road) compared to people walking/running in the park who can leave the trails (even if they rarely do so). Several studies have shown that wildlife disturbance is highly dependent on the type of human activity (Stankowich, 2008, Naylor et al., 2009, Ciuti et al., 2012). For example, Ciuti et al. (2012) showed that large herbivore behaviour is impacted more by humans on foot than bicycles and horses on trails and roads. Further studies on ungulates have shown human avoidance and behavioural changes when close to locations with high human disturbance levels (Shen-Jin et al., 2007, Whittington et al., 2004, Manor and Saltz, 2004). Mountain Gazelles (*Gazella gazelle*), for example, not only actively avoid humans, they have also been shown to alter their flight distance when close to hotspots of human presence (Manor and Saltz, 2004). Similar

results were found in a study by Shen-Jin et al. (2007); fallow deer were observed to increase vigilance rates when close to locations with higher human density, whereas they increased resting time when further away from humans. Our study adds new empirical evidence on the effects of human presence and activity on ungulate behaviour by reporting novel impacts on bedsite selection at a very small spatial scale in a peri-urban setting.

Vehicular disturbance has also been widely documented to impact wildlife behaviour. Noise disturbance created by busy roads, for example, creates a phenomenon called "noise masking". Noise masking impacts communication between individuals in a wide range of taxa. Many studies have shown severe effects on reproductive success, density and community structure as well as anti-predator and foraging behaviour (Barber et al., 2010, Pelletier, 2014, Papouchis et al., 2001, Bonnot et al., 2013). Most ungulates avoid being close to roads, especially when high-traffic levels are present (Pelletier, 2014, Papouchis et al., 2001). For example, a study by Bonnot et al. (2013) showed that roe deer avoid roads even if it compromises their access to important feeding sites. Similar avoidance behaviour has been shown in our study, although we found that, at this limited spatial scale, fallow deer mothers had to balance a trade-off between finding suitable bedsites and keeping a safe distance from roads, which resulted in avoidance of roads being limited to 50m.

Concealment and safety from predators are the top priorities for ungulate mothers when selecting a bedsite to hide their newborns (Barbknecht et al., 2011). This anti-predator strategy manifests in this study through the selection for low visibility habitats for fawns' bedsites. Bongi et al. (2008) showed that lactating roe deer females select for habitats with reduced visibility. Likewise, Ciuti et al. (2006) revealed a preference for dense vegetation and low visibility by fallow deer mothers to hide their fawns from predators. We found that this anti-predator behaviour remains intact even within urban areas. Our study demonstrates consistency in the selection for low visibility when choosing fawns' bedsites across all scales after accounting for the presence of humans on foot (and their dogs) and vehicles on roads. Our findings can therefore inform management decisions when it comes to reducing human pressure on fawning sites within these urban and peri-urban areas. During the fawning season, for instance, hiking trails closer than ~200m to traditional fawning sites should be temporarily closed to minimise disturbance, and

policies regarding keeping dogs on a leash should be enforced. Understory vegetation within forest habitats as well as grasslands should not be cut (which may be a practice in several urban parks to improve human access): in Phoenix Park, for instance, hiking trails are the only linear features where the grassland is managed, therefore promoting use by park visitors, and making it less likely that they will walk in the high grass closer to fawning areas. Knowing the impact that humans are having on wildlife populations living in urban areas is fundamental in order to avoid detrimental effects on wildlife welfare and health. The impacts that we have on wildlife can be minimized by understanding the issues present and creating management plans to mitigate them. In this case, wildlife managers working within urban parks and green spaces can incorporate our findings into management plans in order to promote human-deer coexistence during the birthing season.

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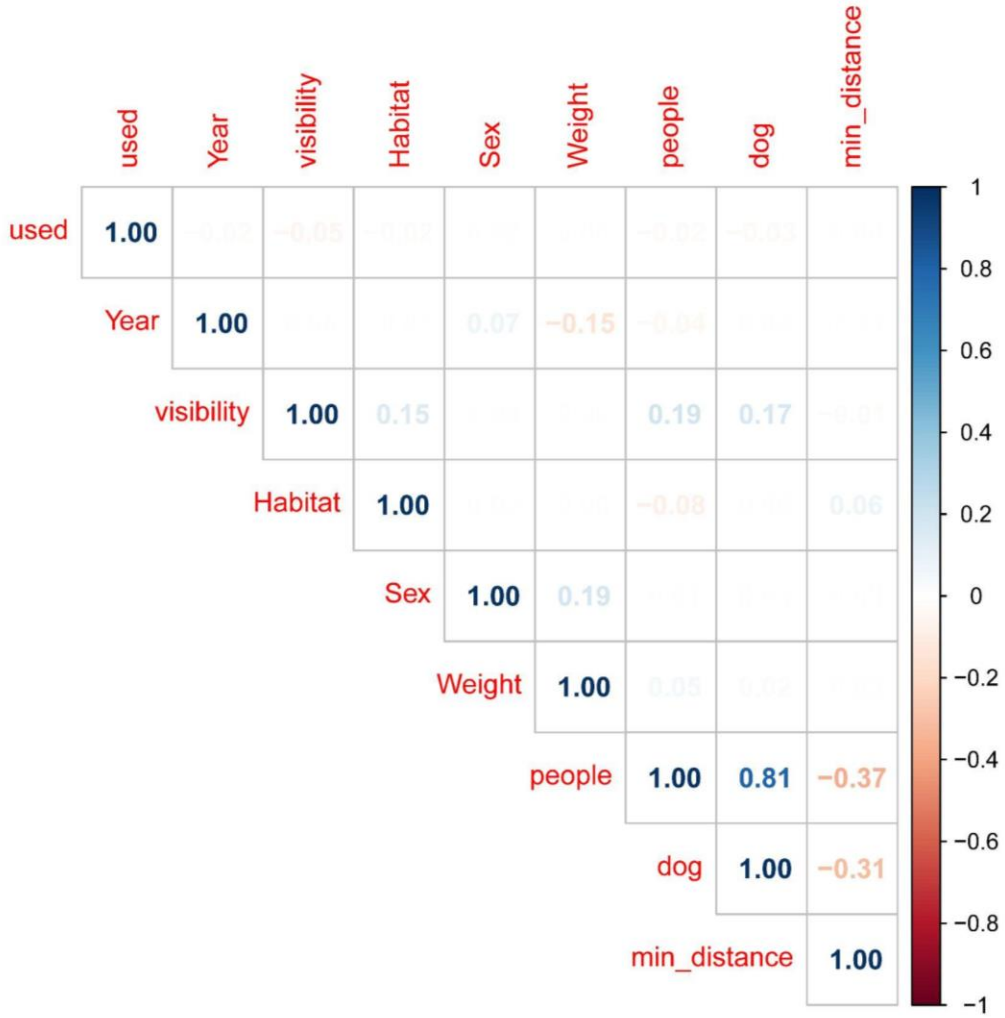
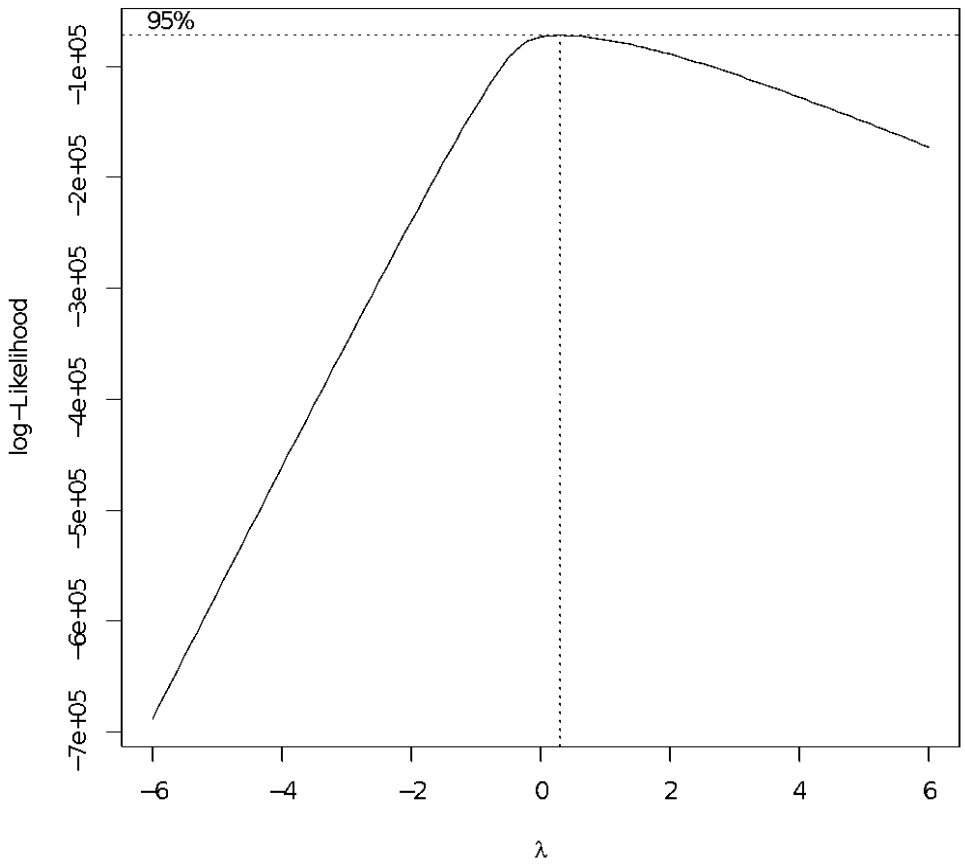
Supplementary Table S1

Collinearity test (Pearson correlation coefficients) of the candidate predictors used to explain bedsite resource selection (presence-available data here labeled as "used"). The sequential colours on the right are associated with the level of correlation between variables with blue indicating a positive correlation (0 to +1) and red a negative correlation (0 to -1). The only variables that were collinear were the predicted number of people (indicating human presence) and likelihood to encounter dogs (indicating canine presence) with a $r_p > 0.7$.



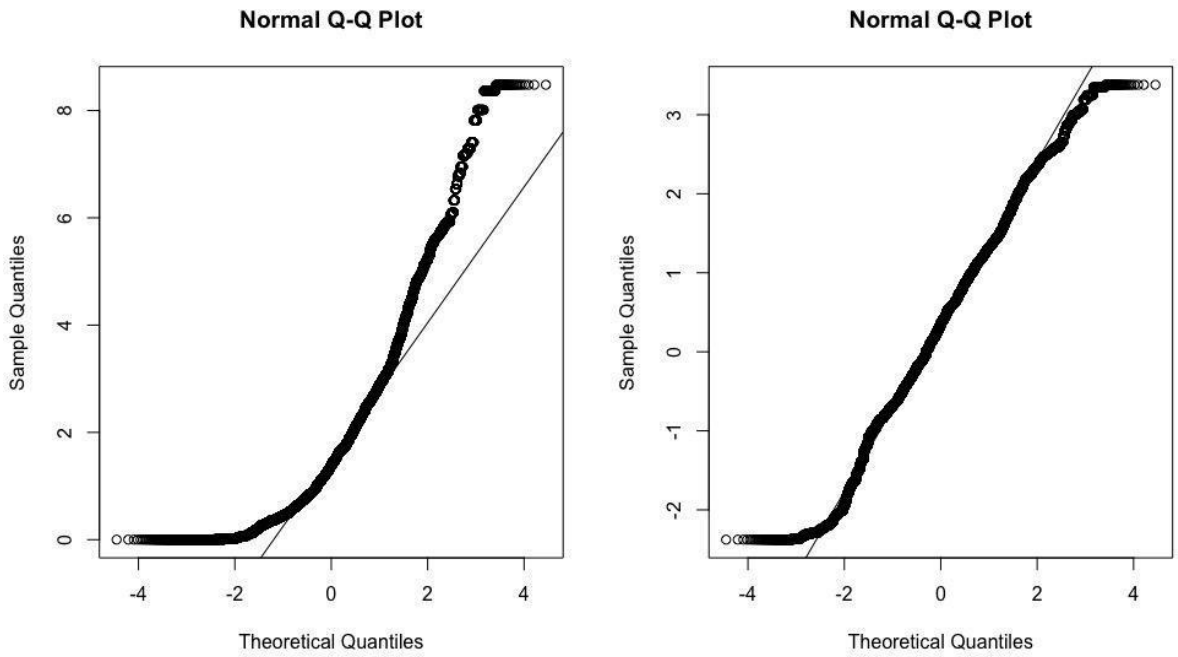
Supplementary Fig. S1

Plot of log-likelihood estimates built to estimate the value of lambda (λ) that achieves the optimal transformation for variable describing the number of park visitors (human presence) at the 50 x 50 m resolution.



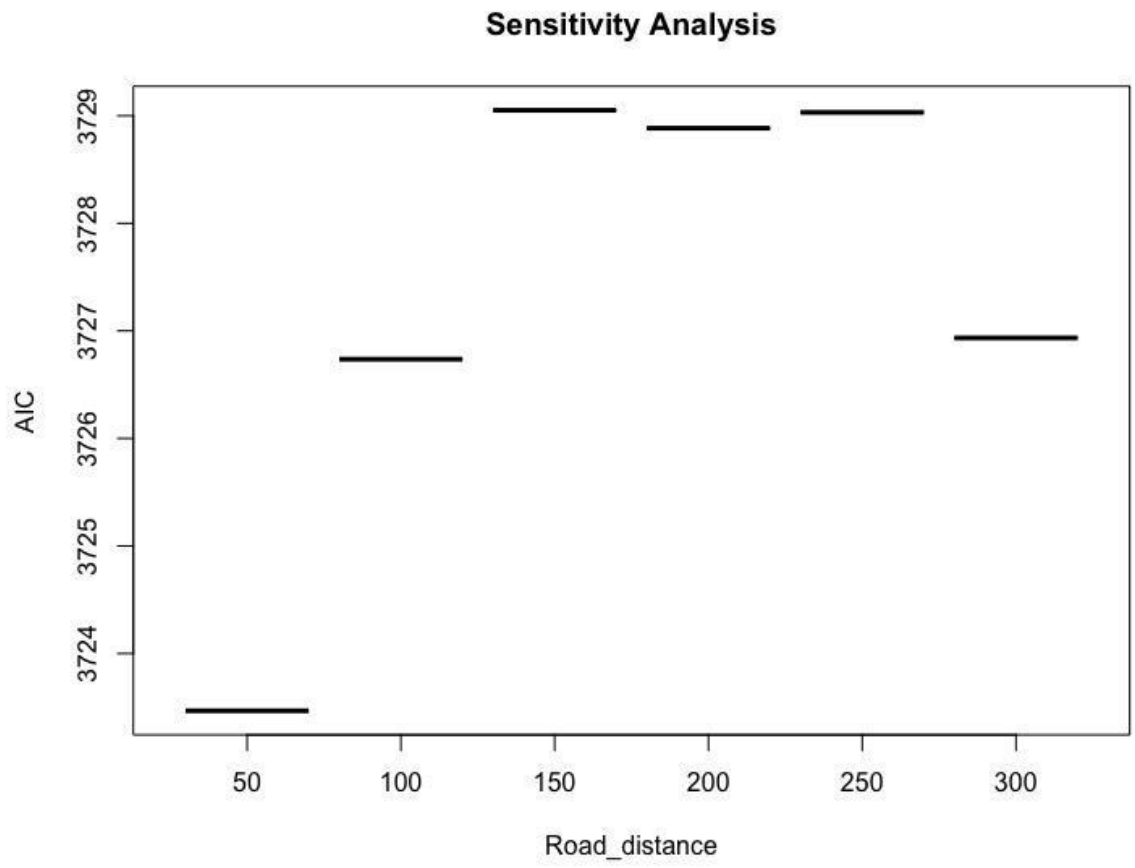
Supplementary Fig. S2

Q-Q Plots of the variable describing the number of park visitors (human presence) before (left) and after (right) transformation with Box.Cox.



Supplementary Fig. S3

AIC values estimated in the sensitivity analyses run to find the best distance threshold (i.e. 50 m) used to categorize the continuous predictor road distance (close: distance < 50m; far: distance >50m).



Supplementary Table S2

GAM Model 1 (human presence) and Model 2 (dog presence) summary.

HUMAN MODEL (response: number of park visitor within 50 x 50 m pixel)

Family: quasipoisson **Link function:** log					
Formula: human presence ~ s(long, lat) + dow					
Parametric coefficients:					
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-12.1318	1.9014	-6.381	2.10e-10	***
Weekend (opposed to weekday)	0.6448	0.1066	6.047	1.71e-09	***
Approximate significance of smooth terms:					
	edf	Ref. df	F	p-value	
s(long, lat)	28.97	29	7.406	<2e-16	***
R-sq(adj) = 0.184			**Deviance explained** = 43.9%		
GCV = 2.1399			**Scale est.** = 5.378		
n = 2484			**Significance: 1 (-) 0.1 (.) 0.05(*) 0.001(**) 0 (***)**		

DOG MODEL (response: presence/absence of dogs within 50 x 50 m pixel)

Family: binomial **Link function:** logit					
Formula: dog presence ~ s(long, lat) + dow					
Parametric coefficients:					
	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-11.2134	2.0431	-5.489	4.05e-08	***
Weekend (opposed to weekday)	0.2989	0.1736	1.721	0.0852	.
Approximate significance of smooth terms:					
	edf	Ref. df	Chi. sq	p-value	
s(long, lat)	28.75	28.98	97.76	2.9e-09	***
R-sq(adj) = 0.12			**Deviance explained** = 26.1%		
UBRE = -0.61285			**Scale est.** = 1		
n = 2484			**Significance: 1 (-) 0.1 (.) 0.05(*) 0.001(**) 0 (***)**		

Supplementary Table S3

GLMMs' model parameters not shown in Table 2

Significance: 1 (-) 0.1 (.) 0.05(*) 0.001(**) 0 (***)

Scale: 250m	*Estimate*	*Std. Error*	*z value*	*Pr (>|z|)*	*Significance*
(Intercept)	-3.39045	0.16137	-21.011	<2e-16	***
Year2019	-0.97618	0.12207	-7.997	1.28e-15	***
Year2020	-1.33774	0.12380	-10.805	<2e-16	***
Sex (Male)	0.02158	0.10011	0.216	0.8293	-
Weight	0.08826	0.31559	0.280	0.7797	-
Weight^2	-0.11144	0.31421	-0.355	0.7228	-
Habitat	0.19751	0.11180	1.767	0.0773	.

Scale: 375m	*Estimate*	*Std. Error*	*z value*	*Pr (>|z|)*	*Significance*
(Intercept)	-4.19019	0.16486	-25.416	<2e-16	***
Year2019	-0.92205	0.11936	-7.725	1.12e-14	***
Year2020	-1.25596	0.12109	-10.372	<2e-16	***
Sex (Male)	-0.01882	0.09882	-0.190	0.84895	-
Weight	0.12149	0.30953	0.393	0.69468	-
Weight^2	-0.12861	0.30585	-0.421	0.67411	-
Habitat	0.03996	0.11115	0.360	0.71920	-

Scale: 500m	*Estimate*	*Std. Error*	*z value*	*Pr (>|z|)*	*Significance*
(Intercept)	-4.72259	0.16948	-27.866	<2e-16	***
Year2019	-0.84347	0.11859	-7.112	1.14e-12	***
Year2020	-1.16764	0.12036	-9.701	<2e-16	***
Sex (Male)	-0.02104	0.09858	-0.213	0.83097	-
Weight	0.18451	0.31099	0.593	0.55298	-
Weight^2	-0.17123	0.30570	-0.560	0.57539	-
Habitat	-0.07963	0.11065	-0.720	0.47174	-

Scale: 750m	*Estimate*	*Std. Error*	*z value*	*Pr (>|z|)*	*Significance*
(Intercept)	-5.32262	0.17222	-30.907	<2e-16	***
Year2019	-0.67398	0.11779	-5.722	1.05e-08	***
Year2020	-1.02082	0.11993	-8.512	<2e-16	***
Sex (Male)	0.02503	0.09787	0.256	0.798154	-
Weight	0.18455	0.31031	0.595	0.552018	-
Weight^2	-0.17166	0.30484	-0.563	0.573343	-
Habitat	-0.20157	0.10875	-1.854	0.063796	.

Scale: 1000m	*Estimate*	*Std. Error*	*z value*	*Pr (>|z|)*	*Significance*
(Intercept)	-5.42690	0.17183	-31-584	<2e-16	***
Year2019	-0.61296	0.11729	-5.226	1.73e-07	***
Year2020	-1.00437	0.11823	-8.424	<2e-16	***
Sex (Male)	0.03033	0.09731	0.312	0.75524	-
Weight	0.17868	0.31252	0.572	0.56750	-
Weight^2	-0.17202	0.30807	-0.558	0.57659	-
Habitat	-0.18012	0.10830	-1.663	0.09628	.

Scale: 1500m	*Estimate*	*Std. Error*	*z value*	*Pr (>|z|)*	*Significance*
(Intercept)	-5.66131	0.17108	-33.091	<2e-16	***
Year2019	-0.65991	0.11699	-5.641	1.69e-08	***
Year2020	-0.95661	0.11931	-8.018	<2e-16	***
Sex (Male)	0.04637	0.09739	0.476	0.6340	-
Weight	0.10977	0.31040	0.354	0.7236	-
Weight^2	-0.11405	0.30691	-0.372	0.7102	-
Habitat	-0.25122	0.10806	-2.325	0.0201	*

Scale: 2500m	*Estimate*	*Std. Error*	*z value*	*Pr (>|z|)*	*Significance*
(Intercept)	-5.77268	0.16877	-34.204	<2e-16	***
Year2019	-0.70036	0.11676	-5.998	1.99e-09	***
Year2020	-0.98314	0.11871	-8.282	<2e-16	***
Sex (Male)	0.03313	0.09717	0.341	0.7331	-
Weight	0.08524	0.31048	0.275	0.7837	-
Weight^2	-0.09228	0.30750	-0.300	0.7641	-
Habitat	-0.22119	0.10763	-2.055	0.0399	*