UNIVERSIDAD DE CHILE

Forestry Sciences and Nature Conservation Faculty Master in Wild Areas and Nature Conservation

OCCUPANCY OF FREE-RANGING DOGS IN RELATION TO INFRASTRUCTURE AND HABITAT ON NAVARINO ISLAND, CAPE HORN BIOSPHERE RESERVE, CHILE

Project degree presented as part of the requirements to qualify for the Master's degree in Wild Areas and Nature Conservation

JUAN ENRIQUE CONTARDO LACLOTE

Veterinarian

SANTIAGO - CHILE 2017

PROJECT DEGREE APPROVAL SHEET

Thesis presented as part of the requirements to qualify for the Master's Degree in Wild Areas and Nature Conservation.

Guide professor	Name	Pedro Cattan
	Grade	
	Signature	
Counselor Professor	Name	Elke Schüttler
	Grade	
	Signature	
Counselor Professor	Name	Cristóbal Briceño
	Grade	
	Signature	
Counselor Professor	Name	Cristian Bonacic
	Grade	
	Signature	

ACKNOWLEDGMENTS

I would like to thank my parents, family and friends for their constant support during the course of this thesis, who always encouraged me to overcome the difficulties faced during this period. I would also like to thank one person in particular who was very important to me and who unfortunately died this year, my grandmother Corina, thank you so much for teaching me to be brave and to persevere in life, I would like to dedicate this work entirely to you.

I am most grateful to Adam Houston, Camila Bravo, Fernando Cárdenas, Felipe Lorenz, Javier Rendoll, Javiera Urrutia, Lorena Saavedra, Nancyrose Houston, Rocío Jara and Valentina Calcagni for their advice, camaraderie and support during my stay in Navarino Island. I am also very grateful to the landowners and the Chilean army who kindly allowed us to carry out our work within their lands. Special thanks go to the Sub-Antarctic Biocultural Conservation Program and all the institutions involved (Omora NGO, North Texas University and Universidad de Magallanes) for the accommodation and materials provided during fieldwork in Puerto Williams.

This study was funded by the Program of Attraction and Insertion of Advanced Human Capital (PAI) of the Chilean National Commission of Scientific and Technological Research (CONICYT, Reference No. 79140024).

INDEX

1.	SUI	MMARY7
2.	INT	RODUCTION
3.	OB.	JECTIVES13
2	2.1	General objective:
2	2.2	Specific objectives:
4.	MA	TERIALS AND METHODS14
4	.1	Study Area14
4	.2	Methodology14
5.	RE	SULTS
5	i.1	Camera traps
5	5.2	Data exploration
6.	DIS	CUSSION
7.	CO	NCLUSION
8.	RE	FERENCES
9.	APF	PENDIX
g).1	Appendix Figures
g).2	Appendix Tables69

INDEX OF FIGURES

Figure 1. Dog awaiting a guanaco to attack it in Bahía Douglas, Navarino Island, southern Chile
Figure 2. Map of the Cape Horn Biosphere Reserve (CHBR)12
Figure 3. Sampling sites for camera-trapping on Navarino Island, southern Chile
Figure 4. Map of habitat type categories of Navarino Island, southern Chile18
Figure 5. Camera trap installation in different types of habitats on Navarino Island, southern Chile.
Figure 6. Distribution of continuous variables displayed in histograms, boxplots, scatter plots and
q-q plots
Figure 7. Distribution of presence data (detected/undetected) and the categorical variable habitat
type shown as frequency of observations for each category40
Figure 8. Relation among continuous detection probability predictor variables with Spearman's
correlation coefficients (r _{oh})
Figure 9. Relation among continuous occupancy predictor variables with Spearman's correlation
coefficients (r _{oh})42
Figure 10. Boxplot about detection data (detected/undetected) for metric continuous variables.
Figure 11. Estimates of detection probability (\widehat{p}) plotted against the respective metric detection
variable values
Figure 12. Estimates of site occupancy $(\widehat{\bm{\psi}})$ plotted against the respective metric occupancy
variable values
Figure A1. Camera trap photographs representing cases of feral dog reproduction on Navarino
Island, southern Chile
Figure A2. Photos of free-ranging dogs captured by camera traps on Navarino Island, southern
Chile
Figure A3. Photographic record of predation of free-ranging dogs on livestock on Navarino Island,
southern Chile
Figure A4. Photographic record of predation of feral dogs on native birds on Navarino Island,
southern Chile
Figure A5. Map about detection data of free-ranging dogs on Navarino Island, southern Chile.68

INDEX OF TABLES

Table 1. Categories for association of domestic dogs with men (adapted from Vanak and Gompper
2009a) and their application to the present study9
Table 2. Summary of all potential predictor variables for occupancy (ψ) and detection probability
(p)22
Table 3. Vertebrate species according to their origin, registered by a camera trap survey on
Navarino Island, southern Chile35
Table 4. Shapiro-Wilk normality test results for all metric continuous variables40
Table 5. VIF values for detection probability and occupancy variables before and after discarding
strongly correlated covariates45
Table 6. Estimated occupancy ($\widehat{m{\psi}}$) and detection probability ($\widehat{m{p}}$) of free-ranging dogs on Navarino
Island, southern Chile47
Table 7. Estimated occupancy ($\widehat{m{\psi}}$) and detection probability ($\widehat{m{p}}$) of free-ranging dogs on Navarino
Island, southern Chile
Table A1. Estimated occupancy ($\widehat{m{\psi}}$) and detection probability ($\widehat{m{p}}$) of free-ranging dogs on Navarino
Island, southern Chile, extended table69

1. SUMMARY

Domestic dogs (Canis familiaris) have turned out to be one of the most common carnivoran species in natural ecosystems worldwide, becoming a major concern for wildlife conservation, particularly on islands. Here, we assessed the effect of infrastructure and the environment on the occupancy probability of free-ranging dogs on Navarino Island, Cape Horn Biosphere Reserve, southern Chile. We collected camera-trap data from 200 sites in a grid around the only major settlement of Navarino Island. Single-season, single species occupancy modeling was used to assess the impact of five infrastructure variables and two environmental variables on the occupancy of free-ranging dog and of six variables on the probability of detection. A total of 4,000 camera-trap days yielded 67 independent photo sequences of free-ranging dogs. Our results provided support for the hypothesis that environmental variables had the most influence on occupancy, when compared to infrastructure variables, while Julian date, survey and animal trail density were the most important predictor variables for detection probability. Free-ranging dogs preferred open habitats instead of forests and habitats at lower elevations. The photographic records further showed interaction between owned/unowned and feral free-ranging dogs as well as reproduction in feral dogs. Dogs were slightly more active at day than at night. Results of the present study demonstrated that there is an urgent need to implement management measurements in order to reduce the numbers of free-ranging dogs in the Cape Horn Biosphere Reserve.

Keywords: biological invasion; camera traps; Canis familiaris, exotic species; subsidized predator

2. INTRODUCTION

Domestic dogs have a cosmopolitan distribution (Aliaga-Rossel et al. 2012), currently being the most abundant carnivore species on earth (Wandeler et al. 1993; Gompper 2014). The global population of domestic dogs has been estimated to be more than 900 million dogs in sympatry with men, equivalent to a 10:1 humand:dog ratio (Hughes and Macdonald 2013; Gompper 2014). In ecosystems where they have become the most abundant carnivore species (Torres and Prado 2010; Krauze-Gryz et al. 2012; Paschoal et al. 2012, 2016; Wierzbowska et al. 2016), they produce important disturbances for people and wildlife (WHO and WSPA 1990).

There is evidence that free-ranging dogs negatively impact wildlife (reviews in Young et al. 2011; Hughes and Macdonald 2013) through harassment (Butler et al. 2004; Atickem et al. 2010; Torres and Prado 2010), and predation (Lacerda et al. 2009; Margalida and Campión 2009; Weber 2010; Aliaga-Rossel et al. 2012). They also hybridize (Green and Gipson 1994; Sillero-Zubiri et al. 2004; Hughes and Macdonald 2013; Lescureux and Linnell 2014) and compete with wild native carnivores (Vanak and Gompper 2009a, 2010; Atickem et al. 2010). Free-ranging dogs are also capable of transmitting disease to wild native carnivores (Roelke-Parker et al. 1996; Cleaveland et al. 2000; Acosta-Jamett 2009). Furthermore, Doherty et al. (2017) demonstrated the extinction of 11 vertebrate species worldwide, as well as the potential threat of 188 species globally, due to free-ranging dogs. Free-ranging dogs also negatively affect human public health (WHO and WSPA 1990; Vaniscotte et al. 2011; Macpherson et al. 2013; Van Kesteren et al. 2013) and livestock producers (Bergman et al. 2009; González et al. 2012; Sepúlveda et al. 2014a; Wierzbowska et al. 2016). Vanak & Gompper (2009) described six categories for the association of domestic dogs with men (Table 1). They vary from owners that have a complete control of their pet dogs (owned dog: they receive all basic care from their owners and their movements are restricted; all other stray dogs are considered free-ranging), till becoming or being totally feral, being able to survive without supplemental provisioning from people (feral dogs).

Table 1. Categories for association of domestic dogs with men (adapted from Vanak and Gompper 2009a) and their application to the present study.

Category	Description	Present study
Owned dogs	Owned dogs confined to a defined outdoor or indoor area	Owned pet dog
Urban free-ranging dogs	Unowned dogs that are commensals, subsisting on garbage and other human derived foods as their primary food source (Beck 1974)	Does not apply
Rural free-ranging dogs	Owned dogs or dogs associated with human households, but not confined to a defined outdoor area	Free-ranging owned dog
Village dogs	Unconfined dogs that are associated with rural households, but rarely leave the immediate vicinity of the village (Vanak 2008)	Free-ranging unowned dog
Feral dogs	Dogs that are completely wild and independent of human derived materials as food sources (Green and Gipson 1994)	Free-ranging feral dog
Wild dogs	Dingoes, feral dogs and their hybrids in Southeast Asia and Australasia with a history of independence from humans and no longer considered domesticated (Sillero-Zubiri et al. 2004)	Does not apply

Surveying terrestrial mammals can be particularly challenging due to their elusive nature, the fact that they often occur at low densities and in many cases, are difficult to distinguish individually (O'Connell et al. 2011). Noninvasive survey methods enable researchers to study such animals across large areas (Long et al. 2007). Technological advances and continued innovation have increased the use of camera-traps for the passive detection of carnivores (Gompper et al. 2006; O'Connell et al. 2011). Occupancy models have proven to be especially useful when studying cryptic and rare species, particularly when other variables, such as abundance become less reliable or impossible to estimate, due to poor data and a low probability of detection (Mackenzie et al. 2006; O'Connell et al. 2006; Linkie et al. 2007). Camera-trapping can be effective for surveying free-ranging dogs (Marks and Duncan 2009). However, camera-trapping studies investigating the ecology of free-ranging dogs are still scarce (Srbek-Araujo and Chiarello 2008;

Paschoal et al. 2012, 2016; Parsons et al. 2016). This same trend seems to replicate in Chile, with only two camera-trapping studies on the ecology of free-ranging dogs (Silva-Rodríguez and Sieving 2012; Moreira-Arce et al. 2015).

The population growth of free-ranging dogs has become a great public issue in the last decade (Bonacic and Abarca 2014), although human:dog ratios are lower than the global estimate (Hughes and Macdonald 2013; Gompper 2014). Based on the previously cited studies (Acosta-Jamett et al. 2010; López et al. 2012; Silva-Rodríguez and Sieving 2012), the Chilean overall dog population is composed by approximately 4,059,200 individuals (Gompper 2014). Free-ranging dogs in Chile affect several mammals classified as Least Concern, Near Threatened, Vulnerable and Endangered by the International Union for Conservation of Nature (IUCN) Red List: culpeo fox (*Lycalopex culpaeus*, Least Concern, CONAF 2012), grey fox (*L. griseus*, Least concern, Silva-Rodríguez and Sieving 2011; Sepúlveda et al. 2014a), guanaco (*Lama guanicoe*, Least Concern, González 2005; CONAF 2012), southern pudu (*Pudu puda*, Near Threatened, Silva-Rodríguez et al. 2009; CONAF 2012), guiña (*Leopardus guigna*, Vulnerable, Sepúlveda et al. 2014a) and patagonian huemul (*Hippocamelus bisulcus*, Endangered, Corti et al. 2010; CONAF 2012). Free-ranging dogs in Chile are also transmitters of canine distemper and parvovirus, impacting populations of grey foxes (González-Acuña et al. 2003; Acosta-Jamett 2009; Acosta-Jamett et al. 2010, 2011) and river otters (*Lontra provocax*, Endangered, Sepúlveda et al. 2014b).

Free-ranging dogs are also present in South America's southernmost ecoregion (Anderson 2014). In the Cape Horn Biosphere Reserve (CHBR) invasive mammal species outnumber their native counterparts (Anderson et al. 2006). Despite of the biocultural importance of this last wilderness area (Mittermeier et al. 2003; Rozzi 2015), information and research on invasive species is mainly focused on beavers (Castor canadensis) (e.g. Anderson et al. 2009) and American mink (Neovison vison) (e.g. Schüttler et al. 2010; Crego et al. 2016). Up to date, there is almost no information about free-ranging dogs. Anderson et al. (2006) provide some records of free-ranging dogs on some islands within the CHBR. Although guanacos are classified as Least Concern by the IUCN Red List, they have suffered a significant population decline on Navarino Island due to multiple causes (González et al. 2002). González (2005) reported fishermen observing freeranging dog packs attacking and frequently predating upon groups of guanacos (L. guanicoe) on Navarino Island, CHBR (Figure 1) and Schüttler et al. (2009) found waterfowl nests destroyed by dogs, particularly of flightless steamer ducks (*Tachyeres pteneres*), an endemic Patagonian duck. Finally, almost half of 138 dogs registered by the Cape Horn Municipality's veterinarian program in Puerto Williams, a village located on the northern coast of Navarino Island, did not have any kind of restriction (Llanos 2013).



Figure 1. Dog awaiting a guanaco to attack it in Bahía Douglas, Navarino Island, southern Chile (Source: González 2005, © Denis Chevally).

The general aim of this study is to estimate occupancy of free-ranging dogs on Navarino Island, in a grid around Puerto Williams, the major human settlement in the CHBR. The influence of infrastructure and habitat on the occupany of free-ranging dogs was specifically investigated. Another aim was to identify and count individuals of free ranging dogs with respect of their categorization of human association (Table 1) within a gradient of more to less human disturbances in the study area.



Figure 2. Map of the Cape Horn Biosphere Reserve (CHBR), modified from Anderson et al. (2006), showing opportunistic monitoring of free-ranging dogs

3. OBJECTIVES

2.1 General objective:

To estimate occupancy of free-ranging dogs in a grid around the major human settlement on Navarino Island.

2.2 Specific objectives:

- Establish the influence of human infrastructure in relation to free-ranging dog occupancy in the study area.
- Determine which kind of habitat are preferred by free-ranging dogs in the study area, and discuss further implications for biodiversity conservation.
- Identify and count individuals of free ranging dogs with respect of their categorization of human association.

4. MATERIALS AND METHODS

4.1 Study Area

The Cape Horn Biosphere Reserve (CHBR) is located at South America's southern tip and belongs to Magallanes XIIth Region (provinces of Tierra del Fuego and Chilean Antarctic), (Rozzi et al. 2006, Figure 2). This reserve consists of an archipelago composed by hundreds of islands, with an approximate total extension of 4,884,274 ha divided into 1,917,238 ha of terrestrial area and 2,967,036 ha of marine area (CONAF 2017). The Cape Horn insular lands ecosystems form part of the Subpolar (or Subantarctic) Evergreen Rain Forest ecoregion (Rozzi et al. 2004b, 2007). The main habitats include evergreen and deciduous forests mainly composed by *Nothofagus betuloides*, *N. pumilio* and *Drimys winteri* (Rozzi et al. 2004a), peatbogs (*Sphagnum* spp.), high Andean habitats, glaciers and snowfields (Pisano 1977).

The core areas of the CHBR include the Alberto d'Agostini and Cape Horn National Parks, which are administered by the National Forestry Corporation (CONAF) (Rozzi et al. 2004b, 2007; Anderson 2014). The buffer areas of the CHBR include the Yendegaia National Park. Puerto Williams, on Navarino Island, is a village located in the Cape Horn Biosphere Reserve (CHBR) and counts 2,932 inhabitants (IMCH 2015). Besides, a small fisher town (Puerto Toro) exists on the eastern coast of Navarino, as well as seven farms (Santa Rosa, Lum, Guerrico, La Estrella, Róbalo, Chaparral and Eugenia) on the northern coast of Navarino Island.

The main economic activities in the province are artisanal fishing, ecotourism and extensive livestock production (Jofré 2006). The CHBR infrastructure is scarce, with only one dirt road that connects the northern coast of Navarino Island. The interior of the island must be reached by the three existing trekking trails, and western, southern and eastern coasts rely on marine transport (Schüttler et al. 2009).

The present study was conducted in a 62.39 km² grid (Figure 3) around Puerto Williams covering different types of habitat and human intervention (infrastructure).

4.2 Methodology

4.2.1 Sampling design

A 200 cells grid with 700 m distance between each grid point was designed, using QGIS Software (Version 2.18.7, QGIS Development Team 2017). Home ranges of free-ranging dogs have been described to vary between 0.4 (Vanak and Gompper 2010; Dürr et al. 2017) and 20.6 km² (Atickem et al. 2010). Site independency could therefore not be ensured spatially, but it was checked whether the same dog appeared in different cameras during one sampling occasion (in the course

of one day) which did not happen. Due to logistic constraints, the sampling points did not surpass 300 meters above sea level (masl), neither did they exceed 4 km from the northern coast. The 200 cells were equally distributed on both sides (100 east and 100 west) of Puerto Williams (Figure 3), since free-ranging dogs are assumed to be concentrated around this town.

4.2.1 Camera traps

Fifty remote cameras (Bushnell Outdoor Products, Overland Park, KS, USA) were installed during four subsequent rotations of 20 days each in order to monitor 200 sampling sites between October 2016 and January 2017. We assumed that this time frame was of sufficient length such that the species was either always present or always absent from the sites or changes occurred randomly, i.e. a closed season (Mackenzie et al. 2006). Each camera was equipped with a passive infrared sensor and an integrated infrared flash (Long et al. 2008). Thus, camera avoidance by animals and risk of theft is considerably reduced compared to a visible flash. The camera was integrated in a single black or camouflaged box, which could be easily handled and fixed to trees or branches. An average of 6.25 camera traps (range 3-7) were installed per day in < 100 m radius around each grid point and coordinates were recorded using a Garmin® Global Position System (GPS) device. The placement of camera traps was decided opportunistically, privileging places near cattle trails, trekking trails and open areas, where the probability that free-ranging dogs transit might be higher than in dense vegetation (Sepúlveda et al. 2015). Camera traps were tied up to trees at an approximate height of 50 cm above ground (Figure 4), which was considered to be a proper height to photograph free-ranging dogs (Moreira-Arce et al. 2015). The surveyor adjusted the right angle of the camera lens and assured a stable camera position. To test the correct adjustment and positioning of the motion sensor and its area covered before the final activation, the test modus of the camera was run and test photos were taken while the observer was walking, crawling, or waving at different distances or heights in front of the camera (Long et al. 2008). To improve detection probability, an olfactory attractant (perforated tuna can, Figure 5) was added in a 2-5 m distance in focus of the camera (Andelt and Woolley 1973; Thorn et al. 2009).

Camera traps were set to shoot three photographs per 30 seconds during the first rotation. However, considering that this yielded a low number of photographs per individual for its further identification, we switched to three photographs per one second for the following 3 rotations. Permits to work on private lands and those administered by the Chilean Navy were acquired with anticipation.

The detection histories of camera traps were recorded using a binary code in which 1 counted as detections and 0 as non-detections within 20 occasions. Nevertheless, sampling occasions were

reduced from 20 to 10 by collapsing data of two consecutive occasions into one. Ten occasions generated reliable estimates of detection probability by reducing the 0 : 1 ratio (Gálvez et al. 2013; Fleschutz et al. 2016). Minimizing zero in the data stabilizes the numerical algorithms used in occupancy modeling (Sunarto et al. 2012).



Figure 3. Sampling sites for camera-trapping on Navarino Island, southern Chile. The grid contains 200 sampling sites with a distance of 700 m in between and was restricted to < 300 masl and < 4 km distance to the coast (due to logistical constraints).



Figure 4. Map of habitat type categories of Navarino Island, southern Chile, used in the present study.



Figure 5. Camera trap installation in different types of habitats on Navarino Island, southern Chile. Camera trap installed in forest habitat, tied up to a lenga beech (A), camera trap installed in grassland habitat, tied up to an Antarctic beech (B), camera trap installed in peatbog habitat, tied up to a vertical log (C), olfactory attractant (canned tuna, D).

4.2.2 Data Preparation and Cartography

Landscape scale metrics were measured within circular 500 m buffers around each camera trap. This buffer size was used following Moreira-Arce et al. (2015) who deployed this buffer on a landscape level when estimating road density for subsequent free-ranging dog occupancy calculation. Land use shapefiles (UNT 2016) classified the habitat of the study area into ten categories: coastal (shore of Navarino Island with sand and rocks), deciduous forest, evergreen forest, mixed forest, pastures, peatbogs, semidense forest, shrubland, succession bog and transition bog. Google Earth[™] (Google Inc. 2017) satellite images were used to reduce those categories to three: (i) forest (comprising deciduous forest, evergreen forest, mixed forest, semidense forest), (ii) peatbogs (comprising peatbogs, succession bog and transition bog) and (iii) shrubland (comprising coastal, pastures and shrubland). Roads and trails were GPS-tracked in the field and edited using the BaseCamp® Software (Garmin Ltd. 2017). Those impossible to be tracked in the field due to having a very large extension were traced in QGIS using Google Earth[™] (Google Inc. 2017) satellite images. The seven existing farms along the northern coast of Navarino Island were included into data analyses since free-ranging dogs from these farms could theoretically enter the grid (Schüttler et al. unpublished data). All further geoprocessing was done using QGIS (Version 2.18.7, QGIS Development Team 2017).

4.2.1 Data processing of photographs of free-ranging dogs

To quantify owned, unowned, and feral free-ranging dogs in the study area, a photographic catalogue of free-ranging dogs in Puerto Williams from 2015/16 (Schüttler et al., unpublished data), was used to classify the photos taken by the camera traps into owned or unowned free-ranging dogs and supposedly feral dogs. As feral dogs were classified those absent in the photographic catalogue, but without knowing whether those dogs were truly feral (i.e., surviving without any human food provisioning including the garbage dump). This photographic catalogue was updated during the sampling period, in which the surveyor walked through the streets of Puerto Williams for four random days, taking pictures of all free-ranging dogs sighted and then classifying them into different categories, according to the association of domestic dog with men (Table 1). Afterwards, free-ranging dogs photographed by camera traps were divided into those three categories (Table 1, third, fourth and fifth categories). Then, the total number of identified individuals were counted per category.

4.2.1 Anaylsis of daylight activity patterns

The daylight activity pattern of free-ranging dogs was analyzed following Sepúlveda et al. (2015), dividing the photoperiod in 4 categories: dawn (±1 h around sunrise), day (between dawn and dusk), dusk (±1 h around sunset) and night (between dusk and dawn). Sunset and sunrise times were adjusted depending on the date registered for each photographic sequence. A Chi-square test was performed to check whether there were significant differences in the daylight activity pattern among free-ranging (owned and unowned) dogs and feral dogs.

4.2.2 Hypotheses for model construction

The identification of suitable predictor variables for occurence of free-ranging dogs was guided by two general hypotheses regarding infrastructure and environmental variables (Table 2). H1-Infrastructure, the presence of owned and unowned free-ranging dogs is usually associated to human settlements (Acosta-Jamett et al. 2010; Silva-Rodriguez et al. 2010; Gompper 2014; Morters et al. 2014; Villatoro et al. 2016), habitually feeding upon human discarded food and garbage (Pal 2003; Campos et al. 2007; Vanak 2008; Vanak and Gompper 2009b; Atickem et al. 2010; Dias et al. 2013) and using trails and roads to access wild habitats (May and Norton 1996; Fiorello et al. 2006; Silva-Rodríguez et al. 2009; Silva-Rodriguez et al. 2010; Doherty et al. 2015; Moreira-Arce et al. 2015; Sepúlveda et al. 2015; Parsons et al. 2016); H2-Environment, freeranging dogs prefer open habitats such as savannas, pastures and shrublands, since they offer little if any resistance to movement, compared to forest habitat, which can act as a clear barrier to the movement of free-ranging dogs (Meek 1999; Vanak 2008; Lacerda et al. 2009; Vanak and Gompper 2010; Sepúlveda et al. 2015). Open habitats like coastal grounds also harbor several species of waterbirds (Schüttler et al. 2009; Couve et al. 2016), while during fieldwork, livestock could be frequently observed in other types of open habitats like pastures, birds and cattle might be possible prey for free-ranging dogs.

The following variables were analysed to test whether infrastructure had a positive effect on the occupancy of free ranging dogs (**H1- Infrastructure**) : distance from Puerto Williams, distance from the nearest farm, distance from the garbage dump, distance from the nearest road/trail and road and trail density (Table 2).

To test whether the environment influences the occupancy of free-ranging dogs (**H2-Environment**). The variables habitat category and height above sea level were analysed (Table 2). Height was included as an additional variable because the pronounced altitudinal gradient in the study area could affect dog occurrence due to possible altitudinal gradients in prey abundance and human activity (Patterson et al. 1989).

Predictor variables	Abbreviation	Level	Unit	Description	References
Ψ, ρ					
H1-Infrastructure					
Distance from Puerto	dist.PW	local	meter	Euclidean distance from	Negative association of the presence
Williams				the core center of Puerto	of free-ranging dogs with distance to
				Williams	human settlements (Srbek-Araujo
					and Chiarello 2008; Soto and
					Palomares 2015)
Distance from the	dist.farm	local	meter	Euclidean distance from	Negative association of the presence
nearest farm				the nearest farm	of free-ranging dogs with distance to
					farm houses (Silva-Rodriguez et al.
					2010).
Distance from the	dist.gdump	local	meter	Euclidean distance from	Free-ranging dogs are usually found
garbage dump				the core center of the	near garbage dumps (Pal 2003;
				garbage dump	Campos et al. 2007; Vanak 2008;
					Vanak and Gompper 2009b; Atickem
					et al. 2010; Dias et al. 2013)
Distance from the	dist.road.trails	local	meter	Euclidean distance from	Negative association of the presence
nearest road/trail				the nearest road or trail	of free-ranging dogs with distance
					from the nearest road (Silva-

Table 2. Summary of all potential predictor variables for occupancy (ψ) and detection probability (p).

Predictor variables	Abbreviation	Level	Unit	Description	References
					Rodriguez et al. 2010; Soto and
					Palomares 2015).
Road and trail	road.trail.dens	landscape	meter/ha	Total road and trail	Positive association of the presence
density				length, within landscape	of free-ranging dogs with road
				extent (500 m buffer)	density (Moreira-Arce et al. 2015).
H2-Environment					
Habitat type	habitat	landscape	categorical	Predominant habitat	Positive association between the
				type within the 500m	presence of free-ranging dogs with
				buffer	open habitats such as savannas,
					pastures, and shrublands, based on
					radiotelemetry locations (Vanak and
					Gompper 2010; Sepúlveda et al.
					2015),.
Height	height	local	meter	Altitude above sea level	Negative association between height
					and occupancy of guiña, lesser
					grison (<i>Galictis cuja</i>), culpeo fox,
					Darwin's fox (Lycalopex fulvipes),
					cougar (<i>Puma concolor</i>) and skunk
					(Conepatus chinga) (Moreira-Arce et
					al. 2015).
p					
Animal trail density	dens.antrails	local	steps/m ²	Total steps when	Not available
				walking along all animal	

Predictor variables	Abbreviation	Level	Unit	Description	References
				trails within a 10 m	
				radius from the camera	
				trap.	
Julian date	julian.date	temporal	numerical	Time specific variable	Positive trend on guiña detection
				(start date 01.01.2016)	probability with Julian date
					(Fleschutz 2013), while it seemed to
					have no effects on the detection
					probability of the Red fox (Vulpes
					vulpes, Sarmento et al. 2011)
Number of animal	n.animtrails	local	number/m ²	Total animal trails	Not available
trails				counted within a 10 m	
				radius from the camera	
				trap	
Rotation	survey	temporal	numerical	Four consecutive	No proved effects in the detection
				rotations	probability of the guiña (Fleschutz
					2013)
Understory density	underst.dens	local	numerical	Understory density	Negative influence of understory
				visibility index, values go	density on detection probability in
				from 0 to 10.	Darwin's fox, cougar and skunk
					(Moreira-Arce et al. 2015).Whereas,
					guiña presence has a positive
					association with understory density

Predictor variables	Abbreviation	Level	evel Unit Description References		References
					(Acosta-Jamett and Simonetti 2004;
					Fleschutz et al. 2016)

4.2.3 Survey specific covariates

Occupancy modeling (MacKenzie et al. 2006) was used to analyse the presence-absence data with each camera representing one site. There are several assumptions that should be met for occupancy modeling (MacKenzie et al. 2006): (1) occupancy status at each site does not change during the sampling season; that is, sites are "closed" to changes in occupancy; (2) the probability of occupancy is constant across the sites, or differences in the probability of occupancy are modeled using covariates; (3) probability of detection is constant between sites and samples, or is a function of site-specific covariates; there is no heterogeneity not modeled in detection probabilities and (4) species detection and detection histories at each location are independent. For modeling detection probability, the following variables were included: animal trail density, Julian date, number of animal trails, survey and understory density (Table 2). Density and number of animal trails could potentially influence the detectability of free-ranging dogs as higher density and number of animal trails could increase detection probability of free-ranging dogs. Julian date was used as a variable to determine whether time specific effects on detection probability exist (Urban and Swihart 2009; Sarmento et al. 2011). To improve the assessment of season specific sampling effects, Julian Date was modified in such way that the day count started with the date January 1st 2016 (jd=0). Like that, Julian Date of the first sampling day (October 11th 2016) was 284, while the last sampling day (Febraury 9th 2017) was 404. Survey was defined as the four independent consecutive sampling rotations which could have an effect on detection, i.e., later rotations could raise the detection probability due to an accumulated experience of the surveyor in the field. Understory density could potentially influence the detectability of free-ranging dogs as higher understory density could prevent detection. It was estimated using Robel pole's technic (Robel et al. 1970; Toledo et al. 2008). A 1.5 m banded plastic pole with 5 cm width intercalated white bands was placed randomly within a 10 m radius from the camera trap and visual obstruction was assessed, counting the visible bands from two different random points at a 4 m distance from the pole. These two measurements were then pooled.

4.2.4 Data exploration

4.2.4.1 Descriptive statistics

Predictor variables for detection and occupancy were examined to detect whether distribution was normal, as well as presence of outliers and collinearity among detection and occupancy covariates separately (Zuur et al. 2009). Statistical calculations were performed using the software program R 3.4.1 (R Core Team 2017).

4.2.4.2 Data normality analysis

Histograms, boxplots, scatter plots and standardized residuals q-q plots were made to test data normality. Histograms were made to check data skewness, boxplots were made to check for outliers, standardized residuals q-q plots were made to check data homoscedasticity (Zuur et al. 2009). On the other hand, histogram and bar plots of categorical variables were made to visualize distributions among classes. Shapiro-Wilk tests were then applied to test data normality.

4.2.4.3 Collinearity among metric variables

Occupancy and detection covariates were checked for collinearity, i.e., the existence of linearly related correlation between covariates (Zuur et al. 2009; Dormann et al. 2013). Correlated metrics probably measure the same aspects of a landscape pattern (O'Neill et al. 1996). Correlations among metric variables were tested using a Pearson correlation matrix (*r*) when data distributed normally, or a Spearman correlation matrix (*r*_{oh}) when covariates lacked data normality. The correlation analysis was done separately for detection probability and occupancy predictor variables. In this study, the threshold of correlation coefficients between predictor variables was *r*/*r*_{oh} > |0.7| (Lantschner et al. 2012) considering that above this value, collinearity severely distort model estimation and subsequent prediction (Dormann et al. 2013). If this was the case, one of the variable pair was excluded from the analysis, while keeping the variable with higher biological importance, accuracy and ease of interpretation.

4.2.4.4 Differences of detected/undetected data for predictor variables

Significant differences of predictor variables mean according to detection (detected/undetected) data were checked using different statistical tests. The two-sample Wilcoxon's rank-sum was used for non-normal distributed predictor variables (Zar 2010). While, the Student's t-test was used for normal distributed predictor variables (Crawley 2007). Differences of metric continuous variables among detection data (detected/undetected), were illustrated through boxplots made for each predictor numeric variable.

4.2.4.5 Differences of detected/undetected data for categorical variables

In order, to test for significant differences of detection data (detected/undetected) among categorical variables (survey and habitat), the Analysis of Variance (ANOVA) test was used for normal distributed detection data, while the Kruskal-Wallis test was used for non-normal distributed detection data. P-values of Kruskal-Wallis tests were adjusted according to Bonferroni if required (df \geq 3) (Crawley 2007).

4.2.4.6 Variance Inflation Factor (VIF) estimation

We might expect VIF > 1 with real data, but would not expect VIF to exceed 4, if model structure is acceptable and only overdispersion is affecting VIF (Burnham and Anderson 2002). Substantially larger values of VIF (say, 6-10) are usually caused partly by a model structure that is inadequate; that is, the fitted model does not account for an acceptable amount of variation in the data (Burnham and Anderson 2002). When data are overdispersed and VIF > 1, the proper likelihood is log(L)/VIF (not just log(L)) (Burnham and Anderson 2002). The estimated overdispersion parameter should generally be $1 \le c \le 4$. Otherwise, some structural lack of fit is probably entering the estimate of overdispersion (Burnham and Anderson 2002).

4.2.4.7 Data transformation of metric variables to z-scores

Metric variables data were transformed to z-scores ($[x - \tilde{x}]/sd$), prior to occupancy modeling (Sunarto et al. 2012; Moreira-Arce et al. 2015). Normalized non-categorical data improves model convergence (Moreira-Arce et al. 2015), avoiding failure by the numerical optimization algorithm used in occupancy modeling (White and Burnham 1999). Furthermore, data transformation reduces the effect of outliers, stabilizes the variance and linearizes relationships (Zuur et al. 2009).

4.2.5 Occupancy models

Single-season, single-species occupancy models were run (Mackenzie et al. 2006) using the Rpackage Unmarked (Fiske and Chandler 2015) of the R Environment (R Core Team 2017). During sampling we considered that two processes occurred: occupancy (ψ) and detection (p). The likelihood based approach of these models introduced by MacKenzie et al. (2002) allows estimating the probability of occupancy and detection probability simultaneously. Occupancy refers to the presence or absence of species at sites during the sampling period (MacKenzie et al. 2006). Detection probability is an aspect of study/sampling protocols that will generally be considered as a noise parameter (MacKenzie et al. 2006). It is natural to consider heterogeneous detection probability models for site occupancy, because factors that influence detectability are many and varied, and it may not be possible to identify, much less control all of them (MacKenzie et al. 2006). Site and survey factors can be included in occupancy modeling as covariates even for sites where individuals of the target species have not been detected (Mackenzie et al. 2002). One of the main differences to other approaches is that MacKenzie et al. (2002) distinguishes if a species is truly absent from a site, during a survey season or if it is present at the site, but simply not detected by the surveyor or surveying methods. Another advantage is that occupancy models take into account heterogenous detection probabilities within calculations (MacKenzie et al. 2006). Thus, model inference is more accurate for occupancy and detectability when modeled as functions of predictor variables, and inference for elusive species is highly improved (Mackenzie et al. 2002). The usual bias of detection plain count data is reduced by including detection probability within the estimates, so non-detection of a species is now modeled as a function of detection probability, which may vary between zero and one (Fleschutz 2013). A detection history (h_i) consists then of the sequence of detections (1) and non-detections (0) of the target species during *K* samplings of site *i* (Mackenzie et al. 2006).

4.2.5.1 Modeling site covariates

Heterogeneous occupancy probability was considered for different sampled sites, this parameter can be modeled as a function of site specific characteristics (Mackenzie et al. 2006). Similarly, detection probability is allowed to vary among sites or surveys, as a function of site or survey specific covariates (Mackenzie et al. 2006). Some forms of detection heterogeneity may be accounted for with covariate information, such as site characteristics or environmental conditions at the time of sampling (Mackenzie et al. 2002). Both occupancy and detection heterogeneity are important to incorporate within models, since unmodeled heterogeneity will introduce bias into parameter estimates (Mackenzie 2005). This covariate information can be easily introduced to the model using a logit function (Mackenzie et al. 2002, 2006).

The purpose of the logit function is to estimate the beta coefficients (β) instead of $\hat{\psi}$ or \hat{p} (MacKenzie et al. 2006). This allows one to estimate the logit of $\hat{\psi}$ or \hat{p} as a linear function with values ranging from \pm^{∞} (Donovan and Hines 2007). The logit function can be expressed by the following equation:

$$logit(\theta_i) = ln\left(\frac{\theta_i}{1-\theta_i}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_U x_{iU}$$

where θ_i is the parameter of interest ($\hat{\psi}$ or \hat{p}) for the *i*th sampling unit and x_{i1} , x_{i2} ,..., x_{iU} , are the values for the *U* covariates of interest measured at the *i*th sampling unit. The regression coefficients

 β_1 , β_2 ,..., β_U determine the effect of the respective covariates, and β_0 is the intercept term (MacKenzie et al. 2006; Donovan and Hines 2007). While the probability of $\hat{\psi}$ or \hat{p} can now vary among sites, the beta coefficients are still assumed to be constant across all sites (MacKenzie et al. 2006). In addition, note that if θ_i is modeled only as a function of β_0 (i.e., if there are no covariates in the model), then $\theta_i=\theta$ for all sites (MacKenzie et al. 2006). Beta coefficients give information on the directionality and magnitude of the effect of covariates on $\hat{\psi}$ or \hat{p} , and are relatively easy to interpret (Donovan and Hines 2007). After incorporating the beta coefficients into the estimates, these remain constant for all sites, allowing $\hat{\psi}$ or \hat{p} to vary among sites (MacKenzie et al. 2006).

Estimates of linear combinations back-transformed to their original scale may be more interesting than direct linear combinations (Fiske and Chandler 2011). This is accomplished by backtransforming logits of $\hat{\psi}$ or \hat{p} to probabilities bound between 0 and 1 for every site (Donovan and Hines 2007). Standard errors of back-transformed estimates of $\hat{\psi}$ or \hat{p} can be also estimated using the delta method (Fiske and Chandler 2011, 2015). Thus, the linear function (logit) is converted back to probabilities (logit link) (Mackenzie et al. 2006):

$$\theta(\psi \text{ or } p) = \frac{\exp(\log it \psi \text{ or } p)}{1 + \exp(\log it \psi \text{ or } p)}$$

If $\hat{\psi}$ is modeled as a function of covariates, the average species presence probability is represented by the following equation:

$$\bar{\psi} \frac{\sum_{i=1}^{N} \hat{\psi}}{N}$$

where *N* represents the number of all surveyed sites (Mackenzie et al. 2002). Precision of models for $\hat{\psi}$ were obtained following Linkie et al. (2006) as $\widehat{SE}/\hat{\psi} \times 100$.

4.2.5.2 Missing observations

Not being able to monitor all sites on all proposed occasions for a target species is a common issue during fieldwork in many wildlife studies (MacKenzie and Bailey 2004). However, these sampling inconsistencies can be easily accommodated using the proposed model likelihood (Mackenzie et al. 2002). Sites with unique combinations of missing values each, must be regarded as separate cohorts to account for missing observations (MacKenzie and Bailey 2004). Site specific covariates can still be included within occupancy and detection estimates for not surveyed sites (Mackenzie et al. 2002). Survey specific covariates can be included within the analyzes only if the site was surveyed during the corresponding occasion (Mackenzie et al. 2002)

4.2.5.3 Model Fitting

A two-step ad hoc approach was used to determine which covariates (Table 2) best predicted occupancy and detection of free-ranging dogs in the study area (MacKenzie et al. 2006; Soto and Palomares 2015; Fleschutz et al. 2016). In a first step, the best fitting predictor variables for detection probability were determined, while occupancy was held constant $\psi(.)$. In the second step, occupancy was modeled, while the selected variables of detection probability were constant. Additionally, one covariate interaction of biological interest (habitat:height), was included within this step. Habitat:height interaction was included into occupancy models because low altitude open habitats might be easily reached by free-ranging dogs, when compared with high closed habitats. All possible covariate combinations for detection probability modeling, as well as for occupancy modeling, were analyzed through data dredging, using package MuMIn (Bartón 2017) from the R Environment (R Core Team 2017).

4.2.5.4 Information-theoretic model selection approach: Akaike's Information Criterion (AIC)

The best model fit was assessed through ranking by AIC (Burnham and Anderson 2002). The AIC is based on the estimate of the expected distance between the Kullback-Leibler (K-L) best model and the fitted model (Burnham and Anderson 2002). For every model the AIC was calculated, the model with the lowest AIC was assumed to be the best fitted model, which is assumed to be the "closest" to the true underlying reality (Burnham and Anderson 2002). The AIC equation is showed below, where *K* is the number of estimable parameters in the approximating model and the maximized log likelihood is $[log(L(\theta|y))]$ (Burnham and Anderson 2002):

$AIC = -2\log[L(\hat{\theta}|y)] + 2K.$

The AIC calculations relies on parsimony, i.e., best fitted models tend to be those with the least number of parameters (Burnham and Anderson 2002). The AIC tradeoff between underfitting (few variables) and overfitting is essential to the principle of parsimony, where the AIC equation first term on the right $(-2log[L(\hat{\theta}|y)])$ tends to decrease as more variables are added to the model, whereas the second term (2K) tends to increase as more parameters are added (Burnham and Anderson 2002).

The value of AIC alone does not give any kind of information, so it must be compared with other AIC values from all candidate models in the set, this difference can be quantified between the best ranked model (Δ AIC = 0) and any given model from the set (Burnham and Anderson 2002). Simple differences of AIC values allow estimates of $E_{\hat{\theta}}[\hat{I}(f,g_i)] - \min E_{\hat{\theta}}[\hat{I}(f,g_i)]$, where the expectation is over the estimated parameters, and min is over the models. The larger the difference between

AIC values, the less plausible it is that the fitted model $g_i(x|\hat{\theta})$ is the K-L best model, given the data *x* (Burnham and Anderson 2002). These differences are known as delta AIC (Δ AIC).

 Δ AIC ≤ 2 values give a substantial level of empirical support of estimated models, Δ AIC values between 4-7 have considerably less support and Δ AIC > 10 have essentially no support (Burnham and Anderson 2002). These Δ AIC values are easy to interpret and allow a quick comparison and ranking of candidate models, and are also useful in computing Akaike weights (Burnham and Anderson 2002).

Model weights (w_i) were calculated to evaluate which of the candidate models was clearly superior to some of the others in the set (Burnham and Anderson 2002). Contrary, multi-model inference was used when there was model selection uncertainty, i.e. no single model with w_i > 0.9, (Burnham and Anderson 2002; Johnson and Omland 2004; Urban and Swihart 2009). Therefore, a set of confidence models were considered to represent the scientific hypotheses of interest by selecting those with better empirical support, i.e. only models with Δ AIC \leq 2.0 (Burnham and Anderson 2002). If $\hat{\theta}$ ($\hat{\psi}$ or \hat{p}) differs noticeably across models then it is risky to base prediction on only one selected model, hence obvious possibility is to compute a weighted estimate of the predicted value, weighting the predictions by the Akaike weights (w_i) (Burnham and Anderson 2002). Model averaged estimates can be expressed by this equation:

$$\widehat{\overline{\theta}} = \sum_{i=1}^{R} w_i \,\widehat{\theta}_i$$

Where $\hat{\theta}$ = model averaged estimate of θ (ψ or p) and w_i = recalculated AIC weights ($\sum w_i = 1$) for each model (Burnham and Anderson 2002). The theoretical, unconditional sampling variance of the estimator of $\hat{\theta}$ is given by (Burnham and Anderson 2002; MacKenzie et al. 2006):

$$Var\left(\hat{\theta}_{A}\right) = \left[\sum_{r=1}^{R} wr \sqrt{Var(\hat{\theta}_{r}|g_{r}) + (\hat{\theta}_{r} - \hat{\theta}_{A})^{2}}\right]^{2}$$

Relative importance of predictor variables for ψ or p can be better estimated by summing the Akaike weights across all the models in the set where variable j occurs (Burnham and Anderson 2002). Therefore, the relative importance of variable j is reflected in the sum $w_{+(j)}$, where as $w_{+(j)}$ increases the more important variable j becomes relative to the rest of the variables. Akaike weights of each model that contained variable j, were summed $w_{+(j)}$ (Burnham and Anderson 2002). Covariates were then ranked according to their relative importance (Burnham and Anderson 2002). Estimated beta coefficients ($\hat{\beta}$) for confidence model set (Δ AIC ≤ 2.0) were used to investigate magnitude and directionality (±) of the effect of the given covariate on $\hat{\psi}$ or \hat{p} . Furthermore, untransformed covariate values were plotted against the logit link function of \hat{p} and

 $\hat{\psi}$ to visualize covariate influence trends on detection and occupancy of free-ranging dogs. R MuMIn package (Bartón 2017) was used for Multi-Model Inference analysis.

4.2.6 Capture-Recapture (CR) models

To estimate the abundance of free-ranging dogs in the study area, capture-recapture (CR) methods were supposed to be used (Williams et al. 2002; O'Connell et al. 2011; Paschoal et al. 2012; Belsare and Gompper 2013). Closed population models use requires that three assumptions must be fulfilled (O'Connell et al. 2011): (1) the population is closed to processes of birth, death, immigration and emigration; (2) there should be no loss of marking methods during the study; (3) and the sources of variation in the probability of detection must be properly identified and calculated.

Spatially explicit CR (SECR) models are a set of CR animal data modeling methods (Efford 2016). These methods are mainly used to estimate population density, but also have advantages over non-spatial methods when estimating population size (Efford 2016). SECR methods overcome border effects that are problematic in the conventional estimation of CR in animal populations (Otis et al. 1978). Primary data for SECR are: (i) the location of detectors (i.e., here camera traps) and (ii) known individuals detections on one or more sampling occasions (i.e., their detection histories) (Efford 2016). In this study, the photographed individuals of free-ranging dogs were recognized according to their phenotype.

5. RESULTS

5.1 Camera traps

Camera-trapping comprised 200 sample sites, for 20 days each, from October 11th 2016 to February 9th 2017. A total of 4,000 camera-trap days recorded 28 vertebrate species, from which 19 were native and nine were introduced (Table 3). The most detected carnivore species in the study area was the American mink (Neovison vison), with at least 52 detections in 200 sampled sites. Meanwhile, the domestic dog was the second most detected carnivore species, with 27 detections in 200 sampled sites. Naïve occupancy, defined as the proportion of sites that recorded at least one photograph of the target species (Tilker 2014), was 0.14 for free-ranging dogs. Camera trap sampling yielded 67 independent photo sequences triggered by 56 dogs. The photographic sequences were considered as independent, as long as they were separated by a minimum of 30 minutes between each other (Fleschutz 2013). From 56 dog records 25 individuals were identified as supposedly feral dogs, 17 individuals as owned free-ranging dogs, and six individuals as unowned free-ranging dogs. Dog individuals could be distinguished by their phenotypic traits; however, eight dogs remained unidentifiable. One female (supposedly feral dog) was identified with two of their lactating puppies. Another female dog (supposedly feral) had clear lactation signs (i.e., mammary glands hypertrophy, Figure A1). If our assumption is correct and those dogs do not rely on human food or shelter, then this is an indication of a reproducing population of feral dogs (as reported by the local community, Schüttler et al. unpublished data). Additionally, interaction between feral and owned free-ranging dogs could be recorded through camera trap images (Figure A2). The daylight activity pattern of free-ranging dogs was not statistically higher during the day (n = 29) than the night (n = 22, X^2 = 2.36, df = 1, p-value = 0.13). Missing observations occurred (n = 91 times out of 4000 sampling occasions) due to failing batteries and technical problems with six camera traps. However, due to the pooling of camera trap histories, missing observations were reduced to n = 45 yielding a final data set of 1955 sampling occasions.

Class	Order	Spanish common name	English common name	Scientific name	Origin
Birds	Anseriformes	Caiquén	Upland Goose	Chloephaga picta	Native
		Pato juarjual	Crested duck	Lophonetta specularioides	Native
		Quetru No Volador	Flightless Steamer-Duck	Tachyeres pteneres	Native
	Cathartiformes	Jote de cabeza colorada	Turkey vulture	Cathartes aura	Native
	Charadriiformes	Gaviota Dominicana	Kelp Gull	Larus dominicanus	Native
		Perdicita Cordillerana Austral	White-bellied Seedsnipe	Attagis malouinus	Native
	Falconiformes	Carancho cordillerano del Sur	White-throated Caracara	Phalcoboenus albogularis	Native
		Tiuque	Chimango Caracara	Milvago chimango	Native
	Passeriformes	Chercán Común	House Wren	Troglodytes aedon	Native
		Chincol	Rufous-collared Sparrow	Zonotrichia capensis	Native
		Churrete Común	Dark-bellied Cinclodes	Cinclodes patagonicus	Native
		Golondrina Chilena	Chilean Swallow	Tachycineta leucopyga	Native
		Loica Común	Long-Tailed Meadowlark	Sturnella loyca	Native
		Rayadito	Thorn-tailed Rayadito	Aphrastura spinicauda	Native
		Tordo	Austral Blackbird	Curaeus curaeus	Native
		Zorzal	Austral Thrush	Turdus falcklandii	Native
	Piciformes	Carpintero Negro	Magellanic Woodpecker	Campephilus magellanicus	Native
	Psittaciformes	Cachaña	Austral Parakeet	Enicognathus ferrugineus	Native
Mammals	Artiodactyla	Oveja	Sheep	Ovis orientalis aries	Introduced
	Artiodactyla	Vaca	Cow	Bos taurus	Introduced
	Carnivora	Gato	Cat	Felis catus	Introduced

Table 3. Vertebrate species according to their origin, registered by a camera trap survey on Navarino Island, southern Chile.

Class	Order	Spanish common name	English common name	Scientific name	Origin
	Carnivora	Perro	Dog	Canis lupus familiaris	Introduced
	Carnivora	Visón	American mink	Neovison vison	Introduced
	Cetartiodactyla	Cerdo	Pig	Sus scrofa domesticus	Introduced
	Perissodactyla	Caballo	Horse	Equus caballus	Introduced
	Rodentia	Castor	Beaver	Castor canadensis	Introduced
	Rodentia	Rata Almizclera	Muskrat	Ondatra zibethicus	Introduced
	Rodentia	Ratón de Hocico Amarillo	Yellow-nosed Field Mouse	Abrothrix xanthorhinus	Native

5.2 Data exploration

5.2.1 Descriptive Statistics

5.2.1.1 Data normality analysis

Results of the explorative statistics revealed that all numeric variables (n = 10) were not normally distributed. This is particularly important for the choice of the subsequent tests. Figure 6 gives a visual overview regarding data distribution, asymmetry and outliers. The variables distance from the nearest farm, distance from the nearest road/trail, height, Julian date, number of animal trails and road and trail density are skewed to the left, whereas understory density is skewed to the right. The boxplots and standardized residual plots illustrate that the distance from the nearest road/trail, height, road and trail density and understory density, each had few extreme values. These extreme values were checked and judged as correct estimates, which justifies keeping them within the subsequent analyzes. On the other hand, the Shapiro-Wilk test yielded that all continuous metric variables were not normally distributed (p<0.05, Table 4).







Figure 6. Distribution of continuous variables displayed in histograms, boxplots, scatter plots and q-q plots.

Shapiro-Wilk normality test						
Variables	W	p-value				
dens.antrails	0.98568	0.040				
dist.farm	0.95926	<0.001				
dist.PW	0.95358	<0.001				
dist.gdump	0.95879	<0.001				
dist.road.trails	0.82817	<0.001				
height	0.92553	<0.001				
julian.date	0.89279	<0.001				
n.animtrails	0.96005	<0.001				
road.trail.dens	0.71507	<0.001				
underst.dens	0.69962	<0.001				

Table 4. Shapiro-Wilk normality test results for all metric continuous variables

5.2.1.2 Distribution of Categorical Variables

The categorical data of the variable habitat type is displayed in bar plots to visualize distributions among classes. Unequal class sizes of habitat type are a result of landscape heterogeneity (Figure 4).



Figure 7. Distribution of presence data (detected/undetected) and the categorical variable habitat type shown as frequency of observations for each category.

5.2.1.3 Collinearity among metric variables

Spearman's correlation coefficients (r_{oh}) were calculated for all numeric variables, since they did not have a normal distribution. Figure 8 illustrates detection probability predictor variable pairs with strong positive or negative correlations ($r_{oh} > |0.7|$), while Figure 9 illustrates occupancy predictor variable pairs with strong positive or negative correlations ($r_{oh} > |0.7|$). All high correlations shown in Figure 8 and Figure **9** are significant at a 95% confidence level (p < 0.05).

The detection predictor variables, animal trail density and number of animal trails were highly correlated ($r_{oh} = -0.91$). Meanwhile, the occupancy predictor variables distance from Puerto Williams and distance from garbage dump were also highly correlated ($r_{oh} = -0.99$), which can be explained because Puerto Williams and its garbage dump are located near each other, being separated by only 1.1 km. To avoid redundancy in variable content, number of animal trails was discarded from the analysis, while animal trail density was kept, even though the latter was not normally distributed (W = 0.98568, p = 0.04037). This decision was taken as the data distribution (e.g. lack of skewness and lack of extreme values) of animal trail density was more reliable when compared to number of animal trails. Likewise, the covariate distance from garbage dump was excluded, while distance to Puerto Williams was kept for analysis, due to its biological importance, since urban centers act as important source of food and shelter for free-ranging dogs (Morters et al. 2014; Villatoro et al. 2016).



Figure 8. Relation among continuous detection probability predictor variables with Spearman's correlation coefficients (r_{oh}).



Figure 9. Relation among continuous occupancy predictor variables with Spearman's correlation coefficients (r_{oh}).

5.2.1.4 Differences of detected/undetected data for predictor variables

Results of the Wilcoxon rank-sum test revealed that presence and absence data were significantly different (p < 0.05) with regard to distance from Puerto Williams, distance from the nearest road/trail, height, and road and trail density (Figure 10). However, results for distance from Puerto Williams should be assessed with caution, since the p-value (p = 0.046) is near the cut-off value.





5.2.1.5 Differences of detected/undetected data for categorical variables

The Kruskal-Wallis rank sum test with Bonferroni corrections did not indicate disparity between habitat types for detected/undetected data at the 0.05 significance level ($X^2 = 3.371$, df = 2, p-value = 0.185), neither for survey ($X^2 = 2.043$, df = 3, p-value = 0.250).

5.2.1.6 Variance Inflation Factor (VIF) estimation

VIF values were calculated using a two-step approach. In a first step, VIF values were calculated for the whole variable set for detection and occupancy, respectively. And in a second step, after discarding strongly correlated variables (i.e., number of animal trails and distance from the garbage dump). VIF values were > 4 among the variable sets for strongly correlated variables (Table 5). However, after discarding number of animal trails for detection probability and distance from the garbage dump for occupancy VIF values ranged between 1-2 (Table 5). Therefore, data overdispersal was not present any more.

Variables	VIF values with correlated	VIF values without correlated
	variables	variables
Detection probability		
julian.date	1.036	1.023
underst.dens	1.063	1.062
dens.antrails	5.980	1.058
n.animtrails	6.017	-
Occupancy		
dist.farm	1.543	1.223
height	1.550	1.443
road.trail.dens	1.667	1.657
dist.road.trails	1.951	1.692
dist.gdump	51.816	-
dist.PW	56.014	1.516

Table 5. VIF values for detection probability and occupancy variables before and after discarding strongly correlated covariates.

5.2.1.7 Data transformation of metric variables to z-scores

Continuous covariates should be transformed in a way that brings their values close to zero in order to improve or even enable numerical convergence of the maximum-likelihood routine (Kéry and Chandler 2012). In this study, all metric variables were transformed to z-scores prior to analysis as they were measured on different scales.

5.3 Occupancy models

5.3.1 Detection probability modeling (first step)

In a first step of analysis, models were fitted with constant occupancy and varying variables for detection probability $\psi(.),p(cov_1+cov_2...+cov_n)$, i.e. animal trail density, Julian date, survey, and understory density. This yielded a total of 16 (2⁴) possible models, including the constant model: $\psi(.),p(.)$ (Table 6).The main interest of this approach was to identify the best predictors of detection probability, for further use in occupancy models. Detection probability was low and ranged between 0.02 and 0.03 (Table 6). As the best ranked model weight was low (w_i = 0.39), multimodel inference ranking was used, yielding (in order from most to least important): Julian date (Σ_{wi} = 1.00), survey (Σ_{wi} = 1.00), animal trail density (Σ_{wi} = 0.45) and understory density (Σ_{wi} = 0.28). Thus, the most important predictor variable combination was julian.date+survey (Table 6). Incorporating these covariates to detection probability increased the occupancy probability by 7%, when comparing the best ranked multivariate detection probability model ($\hat{\psi}$ = 0.229, SE = 0.047) with the constant detection probability estimate ($\hat{\psi}$ = 0.155, SE= 0.029, Table 6).

In contrary to a priori expectations, the time specific covariate Julian date had a negative influence (Figure 11) on the detection of free-ranging dogs ($\beta_1 = -11.54$, SE = 3.030), suggesting that the detection probability decreased with the advancing season. Detection probability increased with latter surveys (survey 2: $\beta_2 = 8.58$, SE = 2.79; survey 3: $\beta_3 = 20.60$, SE = 5.38; survey 4: $\beta_4 = 31.76$, SE = 8.18), indicating that there might have been an improvement of field experience by the surveyor, in concordance with a priori expectations. As expected, a higher animal trail density increased the detection probability of free-ranging dogs ($\beta_2 = 0.258$, SE= 0.203, Figure 11). Contrary to what was expected, understory density had a negative influence on the detection of free-ranging dogs, which diminished as the understory visibility index increased. However, understory density was a poor predictor variable for detection probability, since models containing this variable had a low weight ($\Sigma_{wi} = 0.28$). The direction of impact for all predictor variables was constant as prefixes of beta coefficients (β) of each variable were steady across all substantial models with Δ AIC ≤ 2 .

For further proceedings the second best ranked model: $\psi(.)$,p(julian.date+dens.antrails+survey) was selected to model occupancy probability. This decision was taken as the Δ AIC between the first and second best ranked model was as low as 0.3 and keeping animal trail density in futher occupancy analysis would give a much clearer separation in occupancy model comparisons, since these three variables were good predictors for detection probability of free-ranging dogs.

Table 6. Estimated occupancy $(\hat{\psi})$ and detection probability (\hat{p}) of free-ranging dogs on Navarino Island, southern Chile. First step modeling, where occupancy was held constant in all models. Models were ranked according to Akaike's Information Criterion (AIC). Δ AIC displays the difference between the AIC of a given model to the AIC of the lowest ranked model. W_i represents the model weight, *K* the number of parameters in each model and SE the standard error. Covariates for detection probability and occupancy are given in parentheses. Dots indicate constants.

Model	Κ	AIC	ΔAIC	Wi	$\widehat{\psi}$ (SE)	\hat{p} (SE)
ψ(.),p(julian.date+survey)	6	421.4	0.00	0.390	0.23 (0.04)	0.09 (0.02)
ψ(.),p(julian.date+dens.antrails+survey)	7	421.7	0.34	0.329	0.24 (0.04)	0.09 (0.02)
ψ(.),p(julian.date+survey+underst.dens)	7	423.2	1.87	0.153	0.23 (0.04)	0.09 (0.02)
$\psi(.),p(julian.date+dens.antrails+survey+underst.dens)$	8	423.7	2.30	0.124	0.23 (0.05)	0.08 (0.02)
ψ(.),p(survey+underst.dens)	6	432.2	10.82	0.002	0.19 (0.04)	0.13 (0.03)
ψ(.),p(dens.antrails+survey+underst.dens)	7	434.0	12.57	0.001	0.19 (0.04)	0.13 (0.03)
ψ(.),p(survey)	5	435.1	13.68	0.000	0.19 (0.04)	0.14(0.03)
ψ(.),p(dens.antrails+survey)	6	436.5	15.12	0.000	0.19 (0.04)	0.13 (0.03)
ψ(.),p(underst.dens)	3	436.6	15.19	0.000	0.16 (0.03)	0.19 (0.03)
ψ(.),p(julian.date+underst.dens)	4	436.9	15.52	0.000	0.16 (0.03)	0.19(0.03)
ψ(.),p(dens.antrails+underst.dens)	4	438.3	16.88	0.000	0.16 (0.03)	0.19 (0.03)
ψ(.),p(julian.date+dens.antrails+underst.dens)	5	438.6	17.24	0.000	0.16(0.03)	0.18 (0.03)
ψ(.),p(julian.date)	3	440.9	19.54	0.000	0.16 (0.03)	0.19 (0.03)
ψ(.),p(.)	2	441.9	20.52	0.000	0.16 (0.03)	0.20 (0.03)
ψ(.),p(julian.date+dens.antrails)	4	442.6	21.23	0.000	0.16 (0.03)	0.18 (0.03)
ψ(.),p(dens.antrails)	3	443.7	22.29	0.000	0.16 (0.03)	0.19 (0.03)



Figure 11. Estimates of detection probability (\hat{p}) plotted against the respective metric detection variable values.

5.3.2 Occupancy modeling (second step)

In a second step, models were fitted with fixed detection probability covariates p(julian.date+dens.antrails+survey), and varying predictor variables for occupancy $\psi(cov_1+cov_2+...+cov_n)$. The variables used for occupancy were habitat, height, distance from the nearest farm, distance from Puerto Williams, distance from the nearest road/trail, road and trail density and the interaction habitat:height, yielding a total of 80 possible models, including the constant model: $\psi(.),p(julian.date+dens.antrails+survey)$ (Table A1).

Accounting for detection probability yielded a higher estimate for occupancy ($\hat{\psi} = 0.16$, without variables) than the naïve occupancy ($\hat{\psi} = 0.14$). Incorporating covariates to occupancy increased the occupancy estimate by 76%, if we compare the best ranked occupancy model ($\hat{\psi} = 1.00$, SE = 0.02) to the constant occupancy estimate ($\hat{\psi} = 0.24$, SE= 0.05, Table A1). The set of confidence models (Δ AIC ≤ 2) revealed a detection probability with a narrow range (0.06-0.07), while for occupancy the range was rather broad (0.61-1.00,Table 7). As the best ranked model weight was low ($w_i = 0.14$), multi-model inference ranking was used, yielding (in order from most to least important): habitat ($\Sigma_{wi} = 1.00$), height ($\Sigma_{wi} = 1.00$), distance from the nearest road/trail ($\Sigma_{wi} = 0.69$), habitat:height ($\Sigma_{wi} = 0.50$), distance from Puerto Williams ($\Sigma_{wi} = 0.30$), distance from the nearest farm ($\Sigma_{wi} = 0.30$) and road and trail density ($\Sigma_{wi} = 0.28$). Thus, the most important predictor variable combination for occupancy was dist.road.trails+habitat+height, distance from the nearest road/trail and the interaction term between habitat and height, while poor predictor variables for free-ranging dog occupancy were: distance from Puerto Williams, distance from the nearest farm and road and trail density.

As expected, sites in open habitats were more likely to be occupied than forest sites (peatbog and shrubland, $\beta_2 = 33.19$, SE = 354.39 and $\beta_3 = 0.97$, SE = 1.45 respectively). As previously proposed, height had a negative influence on the occupancy of free-ranging dogs ($\beta_4 = -3.74$, SE = 1.14), which suggests that with higher altitudes occupancy probability decreases (see Figure 12, also for the following covariates). As predicted the interaction between habitat and height indicated that occupancy was higher in open low altitude habitats, like low altitude peatbogs ($\beta_5 = 56.62$, SE = 759.82), and low altitude shrublands ($\beta_6 = 1.75$, SE = 1.65), when compared to high altitude closed habitats, like alpine forests. Contrary to what was expected, dogs had a higher probability to occupy sites farer away from roads and trails ($\beta_1 = 1.22$, SE = 0.68). The direction of impact of all occupancy predictor variables, as well as the interaction between habitat and height, was constant as beta coefficients (β) of each variable were steady across all substantial models with $\Delta AIC \leq 2$.

Table 7. Estimated occupancy ($\hat{\psi}$) and detection probability (\hat{p}) of free-ranging dogs on Navarino Island, southern Chile. Models displayed here ($\Delta AIC \leq 4$) were based on standardized data and were ranked according to Akaike's Information Criterion (AIC). ΔAIC displays the difference between the AIC of a given model to the AIC of the lowest ranked model. W_i represents the model weight, K the number of parameters in each model. Covariates for both occupancy and detection are given in parentheses.

Models	Κ	AIC	$\Delta AIC w_i$	$\widehat{\psi}$ (SE)	<i>p̂</i> (SE)
ψ(distRT+habitat+height+H:H), p(Jdate+denTrail+survey)	13 3	396.1	0.00 0.14	1.00 (0.02)	0.07 (0.02)
ψ(distRT +habitat+height) , p(Jdate+denTrail+survey)	11 3	396.7	0.64 0.10	0.85 (0.15)	0.07 (0.02)
ψ(habitat+height), p(Jdate+denTrail+survey)	10 3	397.3	1.24 0.07	0.62 (0.23)	0.07 (0.02)
ψ(dFarm+ distRT +habitat+height+ H:H),p(Jdate+denTrail+survey)	14 3	397.7	1.56 0.06	1.00 (0.03)	0.06 (0.02)
ψ(drTrails +habitat+height+rtDens+ H:H),p(Jdate+denTrail+survey)	14 3	397.9	1.83 0.06	0.83 (1.25)	0.07 (0.02)
ψ(dPW+ distRT +habitat+height+ H:H),p(Jdate+denTrail+survey)	14 3	398.0	1.85 0.06	0.99 (0.68)	0.07 (0.02)
ψ(dFarm+ distRT + H:H),p(Jdate+denTrail+survey)	12 3	398.3	2.22 0.05	0.88 (0.13)	0.06 (0.02)
ψ(dPW+ distRT + H:H), p(Jdate+denTrail+survey)	12 3	398.5	2.41 0.04	0.86 (0.15)	0.06 (0.02)
ψ(distRT +habitat+height+rtDens), p(Jdate+denTrail+survey)	12 3	398.5	2.44 0.04	0.85 (0.15)	0.07 (0.07)
ψ(habitat+height+ H:H), p(Jdate+denTrail+survey)	12 3	398.6	2.53 0.04	0.17 (0.10)	0.08 (0.02)
ψ(dPW+habitat+height), p(Jdate+denTrail+survey)	11 :	399.0	2.87 0.03	0.69 (0.35)	0.07 (0.02)
ψ(dFarm+habitat+height), p(Jdate+denTrail+survey)	11 :	399.3	3.24 0.03	0.62 (0.24)	0.07 (0.02)
ψ(habitat+height+rtDens), p(Jdate+denTrail+survey)	11 3	399.3	3.24 0.03	0.62 (0.24)	0.07 (0.02)
ψ(dFarm+dPW+ distRT +habitat+height+ H:H), p(Jdate+denTrail+survey)	15 3	399.4	3.30 0.03	1.00 (0.00)	0.06 (0.02)
ψ(dFarm+ distRT +habitat+height+rtDens+ H:H), p(Jdate+denTrail+survey)	15 3	399.6	3.51 0.02	1.00 (0.01)	0.07 (0.02)
ψ(dPW+ distRT +habitat+height+rtDens+H:H), p(Jdate+denTrail+survey)	15 3	399.6	3.52 0.02	1.00 (0.01)	0.07 (0.02)
ψ(dFarm+dPW+ distRT +habitat+height), p(Jdate+denTrail+survey)	13 3	399.8	3.65 0.02	0.92 8(0.11)	0.05 (0.02)

dFarm: distance from de nearest farm; dPW: distance from Puerto Williams, denTrail: animal trail density; distRT: distance from the nearest road/trail; H:H: habitat:height interaction; Jdate: Julian date; rtDens: road and trail density.



Figure 12. Estimates of site occupancy ($\hat{\psi}$) plotted against the respective metric occupancy variable values.

5.4 Capture-Recapture (CR) models

CR models could not be run due to the relatively high number of unidentified individuals (n = 8), which not allowed meeting the CR model assumption regarding individuals should not lose their marks, considering unidentified individuals in the present study could be eventual recaptures. Therefore, these analyses were discarded for the present study.

6. **DISCUSSION**

Primary drivers of occupancy of free-ranging dogs were environmental variables, not variables describing infrastructure. These findings do not match similar studies on owned and unowned free-ranging dogs, where infrastructure variables were the primary drivers to explain occupancy (Srbek-Araujo and Chiarello 2008; Silva-Rodriguez et al. 2010; Moreira-Arce et al. 2015; Soto and Palomares 2015), while studies on feral dogs described them to avoid human settlements (Silva-Rodriguez and Sieving 2011; Krauze-Gryz et al. 2012). The interpretation of the occupancy results of this study is convincing, as records were both, feral dogs (n = 25) and owned/unowned free-ranging dogs (n = 23) and as the above studies show, both categories might behave differently with regard to the parameters in question. Owned and unowned free-ranging dogs in this study seemed to behave similar to feral dogs.

Among the environmental variables, important predictors of occupancy of free-ranging dogs were habitat type and height. Dogs more probably occupied sites in open habitats (coastal, pastures, peatbogs, shrublands, succession bogs and transition bogs) compared to forests. These findings are similar to those described by Lacerda et al. (2009), where owned and unowned free-ranging dog occurrence was strongly associated to open habitats like shrublands and savannas in Brazil. Likewise, Meek (1999) found that owned free-ranging dogs in Australia preferred grasslands over other habitat types. Owned and unowned free-ranging dogs in India were also more present in agricultural land and bare-ground habitats compared to grasslands and plough land (Vanak & Gompper 2010). On the other hand, occupancy models of free-ranging dogs in Poland had no support for habitat variables (Krauze-Gryz et al. (2012), but this might be due to the fact that their study area was heavily impacted by humans, whereas Navarino Island is located in a wilderness setting. The fact that free-ranging owned/unowned and feral dogs in this study preferred shrublands and peatbog habitats might be related to the poor or even lacking resistance to movement in these habitats (Sepúlveda et al. 2015). Additionally, the probably higher presence of livestock in open habitats might be an attraction for owned, unowned and feral free-ranging dogs as prey or carcass (Bergman et al. 2009; Atickem et al. 2010; Silva-Rodriguez et al. 2010) (Figure A3). In this study, dogs also occupied lowland sites with a higher probability than sites at higher altitudes. This might be explained by possible altitudinal gradients in prey abundance (Patterson et al. 1989). There is evidence that on Navarino Island free-ranging dogs prey upon ground-nesting waterbirds (Figure A4) and their eggs (Schüttler et al. 2009). Waterbird species like the Kelp Goose and the Flightless Steamer Duck are strictly coastal (Couve et al. 2016) and some species breed in coastal colonies next to Puerto Williams like Kelp gulls, Dolphin gulls and South American terns (Schüttler et al. 2009). Given the fact that birds are the most diverse and

numerous vertebrate group on Navarino Island (Anderson et al. 2006), coastal waterbirds and their offspring might represent an important and in some cases even naïve prey (Schüttler et al. 2009) for owned/unowned free-ranging and feral dogs.

Our results showed that primary drivers for detection probability were animal trail density, Julian date and survey. In contrary to a priori expectations, the detection probability decreased in parallel to the on-going survey, which could possibly be explained due to the increase of home ranges of free-ranging dogs during warmer weather (Atickem et al. 2010). In later rotations, however, as foreseen, the detection probability increased, most probably due to an improved field experience by the surveyor (see also Fleschutz 2013). Free-ranging dogs were also better detected in sites with a higher animal trail density as those trails probably facilitate the movement and hence, detection of dogs (Fiorello et al. 2006; Sepúlveda et al. 2015; Parsons et al. 2016).

Camera trap detections revealed that there are no significant differences in the daylight activity pattern among the different categories of free-ranging dogs. However, similar studies investigating owned and unowned free-ranging dogs (Paschoal et al. 2012, Moreira-Arce et al. 2015, add Sepulveda 2015) described statictically higher activity during the day when compared with activity during the night. Conversely, Krauze-Gryz et al. (2012) in Poland, and Boitani and Ciucci (1995) in Italy registered more records of feral dogs during the night than during the day.

Our results revealed that there is empirical evidence of a feral dog population on Navarino Island as well as a preference for open habitats in lower altitudes by free-ranging dogs. Owned and unowned free-ranging dogs were registered in three occasions sharing sites with supposedly feral dogs at different times, and in one occasion sharing the same site at the same time. Therefore, we can infer that the home ranges of free-ranging (owned and unowned) dogs and feral dogs overlap in some places, especially in areas surrounding Puerto Williams (records of both dog categories at the same site ranged between 0.48 and 14.76 km from the town, Figure A5). This raises the question whether owned or unowned free-ranging dogs and feral dogs interact in some way, e.g., through cooperative hunting or mating. Further research, for example through GPS monitoring of feral dogs (Claridge et al. 2009) or animal-born cameras (Gerencsér et al. 2013), is needed to better understand these kind of interactions.

American mink were the most recorded carnivore species in this study (n = 353 photos), but were only detected at the same site with dogs twice. There is scientific evidence that invasive species on Navarino Island interact (Crego et al 2016). Future studies could address the possibility of interguild competition between mink and free-ranging dogs as they might influence habitat use by mink (Schüttler et al. 2009). This information would be of substantial interest in the current mink control program of the SAG (SAG and FONDEMA 2008; Caicheo 2010).

54

On Navarino Island, feral dogs seem to reproduce since a female feral dog was photographed with two puppies and another female feral dog had clear signs of lactation (e.g. mammary glands hypertrophy, Figure A1). However, in literature, it is unlikely that free-ranging dog populations are self-sustaining, since they have a rapid population turnover driven by a high juvenile mortality (Butler and Bingham 2000). Free-ranging dog populations could only be maintained by recruitment of free-ranging owned individuals (Daniels and Bekoff 1989) due to poor pet care and husbandry (Butler and Bingham 2000). Further research is needed to determine whether the supposedly feral dog population on Navarino Island is a true feral population of self-sustained and reproducing individuals.

Finally, there were some limitations of this study. (1) Due to the low recapture histories and number of unidentified individuals, capture-mark-recapture analysis could not be performed. This could be improved in the future, following the approach of Paschoal et al. (2016), who placed two camera traps at each site, facing each other. By these means full body photographs might facilitate the identification of individuals. (2) The relatively low detection probability in this study (\hat{p} ranged from 0.02 to 0.07) also limited the access to more data in order to run models for owned/unowned free-ranging dogs and feral dogs separately. As both categories of dogs seem to behave differently regarding infrastructure variables, this would allow to further distinguish between factors affecting the occupancy of owned/unowned dogs and feral dogs, respectively. Hence, to raise the detection probability in future studies, surveying more sites less intensively to produce more precise estimates is advisable (Mackenzie and Royle 2005). And (3) based on a photographic catalogue, photos were classified into owned/unowned free-ranging dogs and feral dogs. However, dogs being absent in town must not necessarily be truly feral dogs as they still might feed on the local landfill. Extending the photographic catalogue to regularly register dogs feeding at the garbage dump might yield a more reliable classification of feral dogs for future studies.

7. CONCLUSION

The results of this study have important implications for the management of free-ranging dogs in the Cape Horn Biosphere Reserve, which is the southernmost protected forest ecoregion of the globe. Forty nine per cent of registered owned dogs (n = 68) did not have any kind of restriction according to the Cape Horn Municipality's veterinarian program (Llanos 2013). Apparently, some of those dogs accessed natural areas within the study area and were photographed by the camera-traps of this study. Therefore, the restriction of movements of owned dogs should be claimed by local authorities, in order to implement the new law on responsible pet ownership (MINSAL 2017). A further suggestion would be to control the unowned dog population in Puerto Williams by chemical castration of male dogs (Garde et al. 2016), since this has been shown to conceivably reduce pregnant females to the point of affecting population growth (Barnett 1986). Considering public health aspects, uncontrolled interactions between livestock and owned/unowned free-ranging dogs might represent a risk of hydatidosis contagion for humans (Jackman and Rowan 2007; Vaniscotte et al. 2011; Van Kesteren et al. 2013). Hydatidosis is an endemic disease for Chile (MINSAL 2015) with no current prevention programs implemented on Navarino Island. Therefore, vaccination and health checks should be stimulated among dog owners of Puerto Williams and dog owners among farmers.

Camera-traps also recorded feral dogs. Feral dogs on Navarino Island might have a higher impact on local biodiversity as per definition they do not feed on human provided food resources or rubbish (Vanak and Gompper 2009a) and can reach high population rates in the absence of predators (Boitani et al. 2017). Therefore, feral dog eradication programs should be planned and implemented on Navarino Island, since natural isolation makes islands ideal places for implementing eradication programs (Capizzi et al. 2010). However, feral dog eradication should be implemented with cautiousness, since unwanted effects (Brooke et al. 2007) might arise such as the mesopredator (Courchamp et al. 1999) and herbivore release effect (Barnett 1986). Under the assumption that feral dogs are established predators in Navarino's local ecosystem, their eradication might lead to an uncontrolled population growth of American mink, beavers and feral cattle. Finally, impacts of free-ranging dogs on the austral biodiversity and interactions between the community of invasive species should be studied urgently to gather a scientific database that informs polictical decisions towards the conservation of the pristiness of the Cape Horn Biosphere Reserve.

8. REFERENCES

- Acosta-Jamett G (2009) The role of domestic dogs in diseases of significance to humans and wildlife health in central Chile. University of Edinburgh
- Acosta-Jamett G, Chalmers WSK, Cunningham AA, et al (2011) Urban domestic dog populations as a source of canine distemper virus for wild carnivores in the Coquimbo region of Chile. Vet Microbiol 152:247–257. doi: 10.1016/j.vetmic.2011.05.008
- Acosta-Jamett G, Cleaveland S, Cunningham AA, Bronsvoort BM (2010) Demography of domestic dogs in rural and urban areas of the Coquimbo region of Chile and implications for disease transmission. Prev Vet Med 94:272–281. doi: 10.1016/j.prevetmed.2010.01.002
- Acosta-Jamett G, Simonetti JA (2004) Habitat use by Oncifelis guigna and Pseudalopex culpaeus in a fragmented forest landscape in central Chile. Biodivers Conserv 13:1135–1151. doi: 10.1023/B
- Aliaga-Rossel E, Ríos-Uzeda B, Ticona H (2012) Amenazas de perros domésticos en la conservación del cóndor, el zorro y el puma en las tierras altas de Bolivia. Rev Latinoam Conserv 2:78–81.
- Andelt WF, Woolley TP (1973) Responses of Urban Mammals to Odor Attractants and a Bait-Dispensing Device. Wildl Soc Bull 2421163:111–118. doi: 10.2307/3782842
- Anderson CB (2014) Lecciones sobre la creación e implementación de la Reserva de la Biósfera Cabo de Hornos como plataforma de investigación de largo plazo. In: Moreira-Muñoz A, Borsdorf A (eds) Reservas de la Biosfera de Chile - Laboratorios para la Sustentabilidad. Academia de Ciencias Austriaca, Pontificia Universidad Católica de Chile, Instituto de Geografía, serie Geolibros, Santiago de Chile, pp 252–267
- Anderson CB, Pastur GM, Lencinas MV, et al (2009) Do introduced North American beavers Castor canadensis engineer differently in southern South America? An overview with implications for restoration. Mamm Rev 39:33–52. doi: 10.1111/j.1365-2907.2008.00136.x
- Anderson CB, Rozzi R, Torres-Mura JC, et al (2006) Exotic vertebrate fauna in the remote and pristine sub-Antarctic Cape Horn Archipelago, Chile. Biodivers Conserv 15:3295–3313. doi: 10.1007/s10531-005-0605-y
- Atickem A, Bekele A, Williams SD (2010) Competition between domestic dogs and Ethiopian wolf (Canis simensis) in the Bale Mountains National Park, Ethiopia. Afr J Ecol 48:401–407. doi: 10.1111/j.1365-2028.2009.01126.x
- Barnett BD (1986) Eradication and control of feral and free-ranging dogs in the Galapagos Islands.
- Bartón K (2017) Multi-Model Inference. 73.
- Beck AM (1974) The Ecology of Stray Dogs: A Study of Free-Ranging Animals, First Edit. Purdue University Press, Indiana
- Belsare A V., Gompper ME (2013) Assessing demographic and epidemiologic parameters of rural dog populations in India during mass vaccination campaigns. Prev Vet Med 111:139–146. doi: 10.1016/j.prevetmed.2013.04.003
- Bergman DL, Breck SW, Bender SC (2009) Dogs gone wild: Feral dog damage in the United States. Proc 13th WDM Conf 117–183.
- Boitani L, Ciucci P (1995) Comparative social ecology of feral dogs and wolves. Ethol Ecol Evol

7:49-72. doi: 10.1080/08927014.1995.9522969

- Boitani L, Francisci F, Ciucci P, Andreoli G (2017) The ecology and behavior of feral dogs: A case study from central Italy. In: Serpell JA (ed) The domestic dog. Its evolution, behavior and interactions with people. Cambridge University Press, Cambridge, pp 342–368
- Bonacic C, Abarca K (2014) Hacia una política y legislación para el control de poblaciones de cánidos y calidad de vida de las personas : un enfoque multidisciplinario Hacia una política y legislación para el control de poblaciones de cánidos y calidad de vida de las. Cent Polit Públicas Pontif Univ Católica Chile 65:11.
- Brooke M de L, Hilton GM, Martins TLF (2007) Prioritizing the world's islands for vertebrateeradication programmes. Anim Conserv 10:380–390. doi: 10.1111/j.1469-1795.2007.00123.x
- Burnham KP, Anderson DR (2002) Model Selection and Multimodel Inference: A Practical Information Theoretic Approach, Second Edi. Springer, New York
- Butler JRA, Du Toit JT, Bingham J (2004) Free-ranging domestic dogs (Canis familiaris) as predators and prey in rural Zimbabwe: Threats of competition and disease to large wild carnivores. Biol Conserv 115:369–378. doi: 10.1016/S0006-3207(03)00152-6
- Butler JR, Bingham J (2000) Demography and dog-human relationships of the dog population in Zimbabwean communal lands. Vet Rec 147:442–446. doi: 10.1136/vr.147.16.442
- Caicheo AMM (2010) Plan de acción para el control del visón norteamericano (Neovison vison), especie invasora en la isla Navarino, Reserva de Biosfera Cabo de Hornos, XIIa Región, Chile. Preparado para el Servicio Agrícola y Ganadero, Magallanes y Antártica Chilena. Informe. Puerto Williams
- Campos CB, Esteves CF, Ferraz KMPMB, et al (2007) Diet of free-ranging cats and dogs in a suburban and rural environment, south-eastern Brazil. J Zool 273:14–20. doi: 10.1111/j.1469-7998.2007.00291.x
- Capizzi D, Baccetti N, Sposimo P (2010) Prioritizing rat eradication on islands by cost and effectiveness to protect nesting seabirds. Biol Conserv 143:1716–1727. doi: 10.1016/j.biocon.2010.04.020
- Claridge AW, Mills DJ, Hunt R, et al (2009) Satellite tracking of wild dogs in south-eastern mainland Australian forests: Implications for management of a problematic top-order carnivore. For Ecol Manage 258:814–822. doi: 10.1016/j.foreco.2009.05.030
- Cleaveland S, Appel MGJ, Chalmers WSK, et al (2000) Serological and demographic evidence for domestic dogs as a source of canine distemper virus infection for Serengeti wildlife. Vet Microbiol 72:217–227. doi: 10.1016/s0378-1135(99)00207-2
- CONAF (2012) ANÁLISIS DE LA OCURRENCIA DE ATAQUES DE PERROS Y GATOS A FAUNA SILVESTRES PROTEGIDA EN EL SISTEMA NACIONAL DE ÁREAS SILVESTRES PROTEGIDAS DEL ESTADO 2007-2012.
- CONAF (2017) Reservas de la Biósfera. http://www.conaf.cl/parques-nacionales/reservas-de-labiosfera/. Accessed 22 Nov 2017
- Corti P, Wittmer HU, Festa-Bianchet M (2010) Dynamics of a small population of endangered huemul deer (*Hippocamelus bisulcus*) in Chilean Patagonia. J Mammal 91:690–697. doi: 10.1644/09-MAMM-A-047.1.Key

Courchamp F, Langlais M, Sugihara G (1999) Cats protecting birds: Modelling the mesopredator release effect. J Anim Ecol 68:282–292. doi: 10.1046/j.1365-2656.1999.00285.x

Couve E, Vidal C, Ruiz J (2016) Aves de Chile, sus Islas Oceánicas y Península Antártica.

- Crawley JM (2007) The R Book, First Edit. John Wiley & Sons Ltd., Chinchester, UK
- Crego RD, Jiménez JE, Rozzi R (2016) A synergistic trio of invasive mammals? Facilitative interactions among beavers, muskrats, and mink at the southern end of the Americas. Biol Invasions 18:1923–1938. doi: 10.1007/s10530-016-1135-0
- Daniels TJ, Bekoff M (1989) Spatial and Temporal Resource Use by Feral and Abandoned Dogs. Ethology 81:300–312. doi: 10.1111/j.1439-0310.1989.tb00776.x
- Dias RA, Guilloux AGA, Borba MR, et al (2013) Size and spatial distribution of stray dog population in the University of São Paulo campus, Brazil. Prev Vet Med 110:263–273. doi: 10.1016/j.prevetmed.2012.12.002
- Doherty TS, Dickman CR, Nimmo DG, Ritchie EG (2015) Multiple threats, or multiplying the threats? Interactions between invasive predators and other ecological disturbances. Biol Conserv 190:60–68. doi: 10.1016/j.biocon.2015.05.013
- Donovan T, Hines J (2007) Exercises in Occupancy Estimation and Modeling. http://www.uvm.edu/envnr/vtcfwru/spreadsheets/occupancy.htm%3E.
- Dormann CF, Elith J, Bacher S, et al (2013) Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography (Cop) 36:027–046. doi: 10.1111/j.1600-0587.2012.07348.x
- Dürr S, Dhand NK, Bombara C, et al (2017) What influences the home range size of free-roaming domestic dogs? Epidemiol Infect 1–12. doi: 10.1017/S095026881700022X
- Efford M (2016) Spatially Explicit Capture-Recapture in R. 1-24.
- Fiorello C V., Noss AJ, Deem SL (2006) Demography, hunting ecology, and pathogen exposure of domestic dogs in the Isoso of Bolivia. Conserv Biol 20:762–771. doi: 10.1111/j.1523-1739.2006.00466.x
- Fiske I, Chandler R (2015) Overview of Unmarked: An R Package for the Analysis of Data from Unmarked Animals. R Dev. Core Team 1–5.
- Fiske IJ, Chandler RB (2011) unmarked: An R package for fitting hierarchical models of wildlife occurrence and abundance. J Stat Softw 43:1–23. doi: 10.1002/wics.10
- Fleschutz M (2013) Impact of fragmentation on Leopardus guigna in the Chilean temperate rainforest. Johannes Gutenberg University Mainz
- Fleschutz MM, Gálvez N, Pe'er G, et al (2016) Response of a small felid of conservation concern to habitat fragmentation. Biodivers Conserv 2016:1447–1463. doi: 10.1007/s10531-016-1118-6
- Gálvez N, Hernández F, Laker J, et al (2013) Forest cover outside protected areas plays an important role in the conservation of the Vulnerable guiña Leopardus guigna. Oryx 47:251–258. doi: 10.1017/S0030605312000099
- Garde E, Pérez GE, Vanderstichel R, et al (2016) Effects of surgical and chemical sterilization on the behavior of free-roaming male dogs in Puerto Natales, Chile. Prev Vet Med 123:106–

120. doi: 10.1016/j.prevetmed.2015.11.011

Garmin Ltd. (2017) BaseCamp software version 4.6.2.

- Gerencsér L, Vásárhelyi G, Nagy M, et al (2013) Identification of Behaviour in Freely Moving Dogs (Canis familiaris) Using Inertial Sensors. PLoS One 8:1–14. doi: 10.1371/journal.pone.0077814
- Gompper ME (2014) Free-Ranging Dogs & Wildlife Conservation, First Edit. Oxford University Press, Oxford
- Gompper ME, Kays RW, Ray JC, et al (2006) A Comparison of Noninvasive Techniques to Survey Carnivore Communities in Northeastern North America Peer Reviewed A Comparison of Noninvasive Techniques to Survey Carnivore Communities in Northeastern North America. Wildl Soc Bull 34:1142–1151.
- González-Acuña D, Ortega Vasquez R, Rivera-Ramírez P, Cabello Cabalin J (2003) Verdacht auf Staupe beim Graufuchs (Pseudalopex griseus) im mittleren Chile (Fallbericht). Z Jagdwiss 49:2–4. doi: 10.1007/s
- González A, Novaro A, Funes M, et al (2012) Mixed-breed guarding dogs reduce conflict between goat herders and native carnivores in Patagonia. Human-Wildlife Interact 6:327–334.
- González BA (2005) SITUACIÓN DE CONSERVACIÓN DE LA POBLACION DE GUANACOS (Lama guanicoe) EN LA COSTA NOR-OESTE DE ISLA NAVARINO, XII REGION.
- González B, Zapata B, Marín JC (2002) Informe Situación de conservación y percepción local sobre la población de guanacos más austral del mundo, Isla Navarino, XII región de Chile.
- Google Inc. (2017) Google Earth[™]. Imag. date Sept. 2017
- Green JS, Gipson PS (1994) Feral dogs. In: Hygnstrom SE, Timm RM, Larson GE (eds) The Handbook: Prevention and Control of Wildlife Damage. University of Nebraska, Lincoln, NE, USA, pp 1–7
- Hughes J, Macdonald DW (2013) A review of the interactions between free-roaming domestic dogs and wildlife. Biol Conserv 157:341–351. doi: 10.1016/j.biocon.2012.07.005
- IMCH (2015) Turismo Sustentable en Cabo de Hornos: Plan de Desarrollo Turístico 2015-2020. Comuna de Cabo de Hornos, Región de Magallanes y Antártica Chilena
- Jackman J, Rowan AN (2007) Free-Roaming Dogs in Developing Countries: The Benefits of Capture, Neuter and Return Programs. In: Salem DJ, Rowan AN (eds) The state of the animals. Human Society Press, Washington, DC, pp 55–78
- Jofré J (2006) RESERVA DE BIOSFERA CABO DE HORNOS. DOCUMENTO BASE PARA LA INCORPORACIÓN DEL TERRITORIO INSULAR DEL CABO DE HORNOS A LA RED MUNDIAL DE RESERVAS DE BIOSFERA. PROGRAMA MAB - UNESCO. Magallania (Punta Arenas) 34:135–140. doi: 10.4067/S0718-22442006000200016
- Johnson JB, Omland KS (2004) Model selection in ecology and evolution. Trends Ecol Evol 19:101–108. doi: 10.1016/j.tree.2003.10.013
- Krauze-Gryz D, Gryz JB, Goszczyński J, et al (2012) The good, the bad, and the ugly: space use and intraguild interactions among three opportunistic predators—cat (Felis catus), dog (Canis lupus familiaris), and red fox (Vulpes vulpes)—under human pressure. Can J Zool 90:1402–1413. doi: 10.1139/cjz-2012-0072

- Lacerda ACR, Tomas WM, Marinho-Filho J (2009) Domestic dogs as an edge effect in the Brasília national park, Brazil: Interactions with native mammals. Anim Conserv 12:477–487. doi: 10.1111/j.1469-1795.2009.00277.x
- Lantschner MV, Rusch V, Hayes JP (2012) Habitat use by carnivores at different spatial scales in a plantation forest landscape in Patagonia, Argentina. For Ecol Manage 269:271–278. doi: 10.1016/j.foreco.2011.12.045
- Lescureux N, Linnell JDC (2014) Warring brothers: The complex interactions between wolves (Canis lupus) and dogs (Canis familiaris) in a conservation context. Biol Conserv 171:232–245. doi: 10.1016/j.biocon.2014.01.032
- Linkie M, Chapron G, Martyr DJ, et al (2006) Assessing the viability of tiger subpopulations in a fragmented landscape. J Appl Ecol 43:576–586. doi: 10.1111/j.1365-2664.2006.01153.x
- Linkie M, Dinata Y, Nugroho A, Haidir IA (2007) Estimating occupancy of a data deficient mammalian species living in tropical rainforests: Sun bears in the Kerinci Seblat region, Sumatra. Biol Conserv 137:20–27. doi: 10.1016/j.biocon.2007.01.016
- Llanos S (2013) Censo de mascotas. 25.
- Long RA, Donovan TM, Mackay P, et al (2007) Comparing Scat Detection Dogs, Cameras, and Hair for surveying carnivores. J Wildl Manage 71:2018–2025. doi: 10.2193/2006-292
- Long RA, Mackay P, Zielinski WJ, Ray JC (2008) Noninvasive survey Methods for Carnivores. Island Press, Washington, DC, USA.
- López J, Abarca K, Bonacic C (2012) Características de las mascotas caninas de cuatro ciudades de Chile. In: XVII Congreso Chileno de Medicina Veterinaria.
- Mackenzie DI (2005) WHAT ARE THE ISSUES WITH PRESENCE ABSENCE DATA FOR WILDLIFE MANAGERS? Special Section : The Value and Utility of Presence – Absence Data to Wildlife Monitoring and Research WHAT ARE THE ISSUES WITH PRESENCE – ABSENCE DATA FOR WILDLIFE MANAGERS? J Wildl Manage 69:849–860. doi: 10.2193/0022-541X(2005)069
- MacKenzie DI, Bailey LL (2004) Assessing the fit of site-occupancy models. J Agric Biol Environ Stat 9:300–318. doi: Doi 10.1198/108571104x3361
- Mackenzie DI, Nichols JD, Lachman GB, et al (2002) Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. Ecology 83:2248–2255.
- Mackenzie DI, Nichols JD, Royle JA, et al (2006) Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Ocurrence, First Edit. Academic Press, London
- MacKenzie DI, Nichols JD, Royle JA, et al (2006) Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Occurrence, First Edit. Elsevier, San Diego, California, USA
- Mackenzie DI, Royle JA (2005) Designing occupancy studies: General advice and allocating survey effort. J Appl Ecol 42:1105–1114. doi: 10.1111/j.1365-2664.2005.01098.x
- Macpherson CNL, Meslin FX, Wandeler AI (2013) Dog Zoonoses and Public Health, First Edit. CABI Publishing, New York
- Margalida A, Campión D (2009) Interacciones agresivas entre buitres leonados Gyps fulvus y ganado: Aspectos ecológicos y económicos de un conflicto emergente. MUNIBE 29:476–

491.

- Marks BK, Duncan RS (2009) Use of Forest Edges by Free-ranging Cats and Dogs in an Urban Forest Fragment. Southeast Nat 8:427–436.
- May SA, Norton TW (1996) Influence of Fragmentation and Disturbance on the Potential Impact of Feral Predators on Native Fauna in Australian Forest Ecosystems. Wildl Res 23:387–400. doi: 10.1071/WR9960387
- Meek PD (1999) The movement, roaming behaviour and home range of free-roaming domestic dogs, Canis lupus familiaris, in coastal New South Wales. Wildl Res 26:847. doi: 10.1071/WR97101
- MINSAL (2017) Ley sobre tenencia responsable de mascotas y animales de compañía. Biblioteca del Congreso Nacional de Chile, Chile
- MINSAL (2015) MANUAL PARA EL DIAGNÓSTICO, TRATAMIENTO, PREVENCIÓN Y CONTROL DE LA HIDATIDOSIS EN CHILE. 47.
- Mittermeier R a, Mittermeier CG, Brooks TM, et al (2003) Wilderness and biodiversity conservation. Proc Natl Acad Sci U S A 100:10309–13. doi: 10.1073/pnas.1732458100
- Moreira-Arce D, Vergara PM, Boutin S (2015) Diurnal human activity and introduced species affect occurrence of carnivores in a human-dominated landscape. PLoS One 10:1–19. doi: 10.1371/journal.pone.0137854
- Morters MK, Mckinley TJ, Restif O, et al (2014) The demography of free-roaming dog populations and applications to disease and population control. J Appl Ecol 51:1096–1106. doi: 10.1111/1365-2664.12279
- O'Connell AF, Karanth KU, Nichols JD (2011) Camera Traps in Animal Ecology: Methods and Analyses. Springer, New York
- O'Connell AF, Talancy NW, Bailey LL, et al (2006) Estimating site occupancy and detection probability parameters for meso- and large mammals in a coastal ecosystem. J Wildl Manage 70:1625–1633. doi: Doi 10.2193/0022-541x(2006)70[1625:Esoadp]2.0.Co;2
- O'Neill R V., Hunsaker CT, Timmins SP, et al (1996) Scale problems in reporting landscape pattern at the regional scale. Landsc Ecol 11:169–180. doi: 10.1007/BF02447515
- Otis DL, Burnham KP, White GC, Anderson DR (1978) Statistical Inference from Capture Data on Closed Animal Populations. Wildl Monogr 62:3–135.
- Pal SK (2003) Urine marking by free-ranging dogs (Canis familiaris) in relation to sex, season, place and posture. Appl Anim Behav Sci 80:45–59. doi: 10.1016/S0168-1591(02)00178-8
- Parsons AW, Bland C, Forrester T, et al (2016) The ecological impact of humans and dogs on wildlife in protected areas in eastern North America. Biol Conserv 203:75–88. doi: 10.1016/j.biocon.2016.09.001
- Paschoal AMO, Massara RL, Bailey LL, et al (2016) Use of Atlantic Forest protected areas by free-ranging dogs: Estimating abundance and persistence of use. Ecosphere 7:1–15. doi: 10.1002/ecs2.1480
- Paschoal AMO, Massara RL, Santos JL, Chiarello AG (2012) Is the domestic dog becoming an abundant species in the Atlantic forest? A study case in southeastern Brazil. Mammalia 76:67–76. doi: 10.1515/mammalia-2012-0501

- Patterson BD, Meserve PL, Lang BK (1989) Distribution and Abundance of Small Mammals along an Elevational Transect in Temperate Rainforests of Chile. J Mammal 70:67–78. doi: 10.2307/1381670
- Pisano E (1977) Fitogeografía de Fuego-Patagonia chilena. I. Comunidades vegetales entre las latitudes 52° y 56° S. An del Inst la Patagon 8:121–250.
- QGIS Development Team (2017) Quantum GIS Geographic Information System. Open Source Geospatial Found. Proj.
- R Core Team (2017) R: A language and environment for statistical computing.
- Robel RJ, Briggs JN, Dayton AD, Hulbert LC (1970) Relationships Between Visual Obstruction Measurements and Weight of Grassland. J Range Manag 295–297.
- Roelke-Parker ME, Munson L, Packer C, et al (1996) A canine distemper virus epidemic in Serengeti lions (Panthera leo). Nature 379:441–445.
- Rozzi R (2015) Primera década de investigación y educación en la Reserva de la Biosfera Cabo de Hornos : el enfoque biocultural del Parque Etnobotánico Omora. An del Inst la Patagon 43:19–43.
- Rozzi R, Charlin R, Ippi S, Dollenz O (2004a) Cabo De Hornos: Un Parque Nacional Libre De Especies Exóticas En El Confín De América. An Inst Patagon 32:55–62.
- Rozzi R, Massardo F, Anderson CB (2004b) Reserva de Biosfera Cabo de Hornos: Una Propuesta de Conservación y Turismo para el Desarrollo Sustentable en el Extremo Austral de América, Ediciones. Punta Arenas
- Rozzi R, Massardo F, Mansilla A, et al (2007) La Reserva De Biosfera Cabo De Hornos e Implementación Del Desarrollo Sustentable Cape Horn Biosphere Reserve : a Challenge for Biodiversity. An del Inst Patagon 35:55–70.
- SAG, FONDEMA (2008) PROGRAMA CONTROL DEL VISÓN EN LA PROVINCIA ANTÁRTICA CHILENA. Punta Arenas
- Sarmento PB, Cruz J, Eira C, Fonseca C (2011) Modeling the occupancy of sympatric carnivorans in a Mediterranean ecosystem. Eur J Wildl Res 57:119–131. doi: 10.1007/s10344-010-0405x
- Schüttler E, Ibarra JT, Gruber B, et al (2010) Abundance and habitat preferences of the southernmost population of mink: Implications for managing a recent island invasion. Biodivers Conserv 19:725–743. doi: 10.1007/s10531-009-9730-3
- Schüttler E, Klenke R, McGehee S, et al (2009) Vulnerability of ground-nesting waterbirds to predation by invasive American mink in the Cape Horn Biosphere Reserve, Chile. Biol Conserv 142:1450–1460. doi: 10.1016/j.biocon.2009.02.013
- Sepúlveda MA, Singer RS, Silva-Rodriguez E, et al (2014a) Domestic dogs in rural communities around protected areas: conservation problem or conflict solution? PLoS One 9:e86152. doi: 10.1371/journal.pone.0086152
- Sepúlveda MA, Singer RS, Silva-Rodríguez EA, et al (2014b) Invasive American mink: Linking pathogen risk between domestic and endangered carnivores. Ecohealth 11:409–419. doi: 10.1007/s10393-014-0917-z

Sepúlveda M, Pelican K, Cross P, et al (2015) Fine-scale movements of rural free-ranging dogs

in conservation areas in the temperate rainforest of the coastal range of southern Chile. Mamm Biol 80:290–297. doi: 10.1016/j.mambio.2015.03.001

Sillero-Zubiri C, Hoffmann M, Macdonald DW (2004) Canids: Foxes, Wolves, Jackals and Dogs.

- Silva-Rodriguez EA, Ortega-Solis GR, Jimenez JE (2010) Conservation and ecological implications of the use of space by chilla foxes and free-ranging dogs in a human-dominated landscape in southern Chile. Austral Ecol 35:765–777. doi: 10.1111/j.1442-9993.2009.02083.x
- Silva-Rodriguez EA, Sieving KE (2011) Influence of Care of Domestic Carnivores on Their Predation on Vertebrates. Conserv Biol 25:808–815. doi: 10.1111/j.1523-1739.2011.01690.x
- Silva-Rodríguez EA, Sieving KE (2012) Domestic dogs shape the landscape-scale distribution of a threatened forest ungulate. Biol Conserv 150:103–110. doi: 10.1016/j.biocon.2012.03.008
- Silva-Rodríguez E, Verdugo C, Aleuy A, et al (2009) Evaluating mortality sources for the Vulnerable pudu Pudu puda in Chile: implications for the conservation of a threatened deer. Oryx 44:97. doi: 10.1017/S0030605309990445
- Soto CA, Palomares F (2015) Human-related factors regulate the presence of domestic dogs in protected areas. Oryx 49:254–260. doi: 10.1017/S0030605313000604
- Srbek-Araujo AC, Chiarello AG (2008) Domestic dogs in Atlantic forest preserves of south-eastern Brazil: a camera-trapping study on patterns of entrance and site occupancy rates. Brazilian J Biol 68:771–779. doi: 10.1590/S1519-69842008000400011
- Sunarto S, Kelly MJ, Parakkasi K, et al (2012) Tigers need cover: Multi-scale occupancy study of the big cat in Sumatran forest and plantation landscapes. PLoS One. doi: 10.1371/journal.pone.0030859
- Thorn M, Scott DM, Green M, et al (2009) Estimating Brown Hyaena Occupancy Using Baited Camera Traps. South African J Wildl Res 39:1–10. doi: 10.3957/056.039.0101
- Tilker ABS (2014) Estimating Site Occupancy for Four Threatened Mammals in Southeastern Laos. University of Texas
- Toledo D, Abbott LB, Herrick JE (2008) Cover Pole Design for Easy Transport, Assembly, and Field Use. J Wildl Manage 72:564–567. doi: 10.2193/2007-109
- Torres PC, Prado PI (2010) Domestic dogs in a fragmented landscape in the Brazilian Atlantic Forest: abundance, habitat use and caring by owners. Brazilian J Biol 70:987–994. doi: 10.1590/S1519-69842010000500010
- UNT (2016) Sub-Antarctic Biocultural Conservation Program. https://chile.unt.edu/.
- Urban NA, Swihart RK (2009) Multiscale perspectives on occupancy of meadow jumping mice in landscapes dominated by agriculture. J Mammal 90:1431–1439. doi: 10.1644/08-MAMM-A-393R.1
- Vanak AT (2008) Intraguild Interactions between native and domestic carnivores in central India. University of Missouri
- Vanak AT, Gompper ME (2009a) Dogs canis familiaris as carnivores: Their role and function in intraguild competition. Mamm Rev 39:265–283. doi: 10.1111/j.1365-2907.2009.00148.x

Vanak AT, Gompper ME (2010) Interference competition at the landscape level: The effect of free-

ranging dogs on a native mesocarnivore. J Appl Ecol 47:1225–1232. doi: 10.1111/j.1365-2664.2010.01870.x

- Vanak AT, Gompper ME (2009b) Dietary Niche Separation Between Sympatric Free-Ranging Domestic Dogs and Indian Foxes in Central India. J Mammal 90:1058–1065. doi: 10.1644/09-MAMM-A-107.1
- Van Kesteren F, Mastin A, Mytynova B, et al (2013) Dog ownership, dog behaviour and transmission of Echinococcus spp. in the Alay Valley, southern Kyrgyzstan. Parasitology 140:1674–1684. doi: 10.1017/S0031182013001182
- Vaniscotte A, Raoul F, Poulle ML, et al (2011) Role of dog behaviour and environmental fecal contamination in transmission of Echinococcus multilocularis in Tibetan communities. Parasitology 138:1316–1329. doi: 10.1017/S0031182011000874
- Villatoro FJ, Sepúlveda MA, Stowhas P, Silva-Rodríguez EA (2016) Urban dogs in rural areas: Human-mediated movement defines dog populations in southern Chile. Prev Vet Med 135:59–66. doi: 10.1016/j.prevetmed.2016.11.004
- Wandeler AI, Matter HC, Kappeler A, Budde A (1993) The ecology of dogs and canine rabies: a selective review. Rev Sci Tech 12:51–71.
- Weber M (2010) Perros (Canis lupus familiaris) y gatos (Felis catus) ferales en la Reserva de la Biosfera Los Petenes, Campeche, México: Diagnóstico, efectos en la fauna nativa y perspectivas de control. San Francisco de Campeche
- White GC, Burnham KP (1999) Program mark: Survival estimation from populations of marked animals. Bird Study 46:S120–S139. doi: 10.1080/00063659909477239
- WHO, WSPA (1990) Guidelines for Dog Population Management.
- Wierzbowska IA, Hędrzak M, Popczyk B, et al (2016) Predation of wildlife by free-ranging domestic dogs in Polish hunting grounds and potential competition with the grey wolf. Biol Conserv 201:1–9. doi: 10.1016/j.biocon.2016.06.016
- Williams BK, Nichols JD, Conroy MJ (2002) Analysis and Management of Animal Populations, Academic P. San Diego, California, USA
- Young JK, Olson KA, Reading RP, et al (2011) Is Wildlife Going to the Dogs? Impacts of Feral and Free-roaming Dogs on Wildlife Populations. Bioscience 61:125–132. doi: 10.1525/bio.2011.61.2.7
- Zar J (2010) Biostatistical analysis, Fifth edit. Prentice Hall Inc., New Jersey
- Zuur AF, Ieno EN, Elphick CS (2009) A protocol for data exploration to avoid common statistical problems. Methods Ecol Evol 1–12. doi: 10.1111/j.2041-210X.2009.00001.x

9. APPENDIX

9.1 Appendix Figures



Figure A1. Camera trap photographs representing cases of feral dog reproduction on Navarino Island, southern Chile. Female feral dog with its puppy (A) and another female feral dog with mammary gland hypertrophy (B).



Figure A2. Photos of free-ranging dogs captured by camera traps on Navarino Island, **southern Chile.** Feral dog (A), owned free-ranging dog (B), unowned free-ranging dog (C) and interaction between an owned free-ranging dog (at the back) and a feral dog (at the front) (D).



Figure A3. Photographic record of predation of free-ranging dogs on livestock on Navarino Island, southern Chile. Dead calf killed by a free-ranging dog (A, ©Elke Schüttler) and a free-ranging dog eating from a dead cow carcass (B, © Cristián Soto).



Figure A4. Photographic record of predation of feral dogs on native birds on Navarino Island, southern Chile. Owned free-ranging dog killing an adult individual of Upland goose (*Chloephaga picta*) (A, ©Jaime Jiménez) and an adult individual of Crested duck (*Lophonetta specularioides*) killed by a free-ranging dog (B, © Nancyrose Houston).



Figure A5. Map about detection data of free-ranging dogs on Navarino Island, southern Chile. Free-ranging dog categories and their combinations at sampling sites are explained in the legend.

9.2 Appendix Tables

Table A1. Estimated occupancy ($\hat{\psi}$) and detection probability (\hat{p}) of free-ranging dogs on Navarino Island, southern Chile, extended table. Models were based on standardized data and were ranked according to Akaike's Information Criterion (AIC). Δ AIC displays the difference between the AIC of a given model to the AIC of the lowest ranked model. W_i represents the model weight, *K* the number of parameters in each model and SE the standard error. Covariates for detection probability and occupancy are given in parentheses. Dots indicate constants.

Model	Κ	AIC	ΔAIC	Wi	$\widehat{\psi}$	(SE)	\hat{p}	(SE)
ψ(distRT +habitat+height+H:H), p(Jdate+densTrail+survey)	13	396.1	0.00	0.14	1.00	(0.02)	0.07	(0.02)
ψ(distRT+habitat+height), p(Jdate+densTrail+survey)	11	396.7	0.64	0.10	0.85	(0.15)	0.07	(0.02)
ψ(habitat+height), p(Jdate+densTrail+survey)	10	397.3	1.24	0.07	0.62	(0.23)	0.08	(0.02)
ψ(dFarm+distRT+habitat+height+H:H), p(Jdate+densTrail+survey)	14	397.7	1.56	0.06	1.00	(0.03)	0.06	(0.02)
ψ(distRT+habitat+height+rtDens+H:H), p(Jdate+densTrail+survey)	14	397.9	1.83	0.06	0.83	(1.25)	0.07	(0.02)
ψ(dPW+distRT +habitat+height+H:H), p(Jdate+densTrail+survey)	14	398.0	1.85	0.06	0.99	(0.68)	0.07	(0.02)
ψ(dFarm+distRT+habitat+height), p(Jdate+densTrail+survey)	12	398.3	2.22	0.05	0.88	(0.13)	0.06	(0.02)
ψ(dPW+distRT+habitat+height), p(Jdate+densTrail+survey)	12	398.5	2.41	0.04	0.86	(0.15)	0.06	(0.02)
ψ(distRT+habitat+height+rtDens), p(Jdate+densTrail+survey)	12	398.5	2.44	0.04	0.85	(0.15)	0.07	(0.07)
ψ(habitat+height+H:H), p(Jdate+densTrail+survey)	12	398.6	2.53	0.04	0.18	(0.10)	0.09	(0.02)
ψ(dPW+habitat+height), p(Jdate+densTrail+survey)	11	399.0	2.87	0.03	0.69	(0.35)	0.07	(0.02)
ψ(dFarm+habitat+height), p(Jdate+densTrail+survey)	11	399.3	3.24	0.03	0.62	(0.24)	0.08	(0.02)
ψ(habitat+height+rtDens), p(Jdate+densTrail+survey)	11	399.3	3.24	0.03	0.62	(0.24)	0.08	(0.02)
ψ(dFarm+dPW+distRT+habitat+height+H:H), p(Jdate+densTrail+survey)	15	399.4	3.30	0.03	1.00	(0.00)	0.06	(0.02)
ψ(dFarm+distRT +habitat+height+rtDens+H:H), p(Jdate+densTrail+survey)	15	399.6	3.51	0.02	1.00	(0.01)	0.07	(0.02)
ψ(dPW+distRT +habitat+height+rtDens+H:H), p(Jdate+densTrail+survey)	15	399.6	3.52	0.02	1.00	(0.01)	0.07	(0.02)
ψ(dFarm+dPW+distRT+habitat+height), p(Jdate+densTrail+survey)	13	399.8	3.65	0.02	0.92	(0.11)	0.05	(0.02)
ψ(dPW+distRT+habitat+height+rtDens), p(Jdate+densTrail+survey)	13	400.1	4.02	0.02	0.86	(0.15)	0.06	(0.02)
ψ(dPW+habitat+height+H:H), p(Jdate+densTrail+survey)	13	400.2	4.12	0.02	0.18	(0.10)	0.08	(0.02)
ψ(dFarm+distRT +habitat+height+rtDens), p(Jdate+densTrail+survey)	13	400.3	4.17	0.02	0.87	(0.14)	0.06	(0.02)
ψ(dFarm+habitat+height+H:H), p(Jdate+densTrail+survey)	13	400.5	4.44	0.02	0.17	(0.09)	0.09	(0.02)
ψ(habitat+height+rtDens+H:), p(Jdate+densTrail+survey)	13	400.6	4.52	0.01	0.18	(0.10)	0.08	(0.02)
ψ(dFarm+dPW+habitat+height+rtDens), p(Jdate+densTrail+survey)	12	400.9	4.83	0.01	0.71	(0.50)	0.07	(0.03)

Model	Κ	AIC	ΔAIC	Wi	$\hat{\psi}$	(SE)	ŷ	(SE)
ψ(dPW+habitat+height+rtDens), p(Jdate+densTrail+survey)	12	400.9	4.84	0.01	0.68	(0.36)	0.07	(0.02)
ψ(dFarm+dPW+distRT +habitat+height+rtDens+H:H), p(Jdate+densTrail+survey)	16	401.3	5.20	0.01	1.00	(0.01)	0.06	(0.02)
ψ(dFarm+habitat+height+rtDens), p(Jdate+densTrail+survey)	12	401.3	5.24	0.01	0.63	(0.26)	0.07	(0.02)
ψ(dFarm+dPW+distRT +habitat+height+rtDens), p(Jdate+densTrail+survey)	14	401.6	5.54	0.01	0.92	(0.12)	0.05	(0.02)
ψ(dFarm+dPW+habitat+height+H:H), p(Jdate+densTrail+survey)	14	402.1	6.04	0.01	0.17	(0.10)	0.08	(0.03)
ψ(dPW+habitat+height+rtDens+H:H), p(Jdate+densTrail+survey)	14	402.2	6.10	0.01	0.18	(0.10)	0.08	(0.02)
ψ(dFarm+habitat+height+rtDens+H:H), p(Jdate+densTrail+survey)	14	402.5	6.44	0.01	0.17	(0.09)	0.09	(0.03)
ψ(dFarm+dPW+habitat+height+rtDens), p(Jdate+densTrail+survey)	13	402.9	6.82	0.01	0.71	(0.50)	0.07	(0.03)
ψ(dFarm+dPW+habitat+height+rtDens+H:H), p(Jdate+densTrail+survey)	15	404.1	7.99	0.00	0.17	(0.10)	0.08	(0.03)
ψ(height), p(Jdate+densTrail+survey)	8	409.0	12.92	0.00	0.19	(0.05)	0.09	(0.02)
ψ(height+rtDens), p(Jdate+densTrail+survey)	9	410.7	14.58	0.00	0.19	(0.05)	0.09	(0.02)
ψ(dPW+height+rtDens), p(Jdate+densTrail+survey)	9	410.9	14.80	0.00	0.19	(0.05)	0.08	(0.02)
ψ(dFarm+height), p(Jdate+densTrail+survey)	9	411.0	14.90	0.00	0.19	(0.05)	0.09	(0.03)
ψ(distRT+height), p(Jdate+densTrail+survey)	9	411.0	14.91	0.00	0.19	(0.05)	0.09	(0.02)
ψ(dPW+height+rtDens), p(Jdate+densTrail+survey)	10	412.3	16.23	0.00	0.19	(0.05)	0.08	(0.02)
ψ(dFarm+height+rtDens), p(Jdate+densTrail+survey)	10	412.6	16.50	0.00	0.18	(0.05)	0.09	(0.03)
ψ(distRT+height+rtDens), p(Jdate+densTrail+survey)	10	412.7	16.58	0.00	0.19	(0.05)	0.09	(0.02)
ψ(dPW+distRT+height), p(Jdate+densTrail+survey)	10	412.9	16.76	0.00	0.19	(0.05)	0.08	(0.02)
ψ(dFarm+dPW+height), p(Jdate+densTrail+survey)	10	412.9	16.77	0.00	0.19	(0.06)	0.08	(0.03)
ψ(dFarm+distRT+height), p(Jdate+densTrail+survey)	10	413.0	16.88	0.00	0.19	(0.06)	0.09	(0.03)
ψ(dFarm+dPW+height+rtDens), p(Jdate+densTrail+survey)	11	414.2	18.05	0.00	0.19	(0.05)	0.09	(0.03)
ψ(dPW+distRT +height+rtDens), p(Jdate+densTrail+survey)	11	414.3	18.23	0.00	0.19	(0.05)	0.08	(0.02)
ψ(dFarm+distRT +height+rtDens), p(Jdate+densTrail+survey)	11	414.6	18.49	0.00	0.18	(0.05)	0.09	(0.03)
ψ(dFarm+dPW+distRT +height), p(Jdate+densTrail+survey)	11	414.8	18.71	0.00	0.19	(0.06)	0.09	(0.03)
ψ(dFarm+dPW+distRT +height+rtDens), p(Jdate+densTrail+survey)	12	416.2	20.05	0.00	0.19	(0.05)	0.09	(0.03)
ψ(dFarm+habitat+rtDens), p(Jdate+densTrail+survey)	11	417.2	21.10	0.00	0.33	(0.11)	0.09	(0.02)
ψ(distRT), p(Jdate+densTrail+survey)	8	417.6	21.49	0.00	0.18	(0.05)	0.09	(0.03)
ψ(habitat+rtDens), p(Jdate+densTrail+survey)	10	417.9	21.84	0.00	0.35	(0.12)	0.08	(0.02)
ψ(distRT+hábitat), p(Jdate+densTrail+survey)	10	418.0	21.91	0.00	0.21	(0.09)	0.09	(0.03)

Model	K	AIC	ΔAIC	Wi	$\widehat{\psi}$ (SE)	ĝ	(SE)
ψ(rtDens), p(Jdate+densTrail+survey)	8	418.0	21.93	0.00	0.23 (0.05)	0.09	(0.02)
ψ(dFarm+distRT+habitat), p(Jdate+densTrail+survey)	11	418.2	22.06	0.00	0.27 (0.10)	0.10	(0.03)
ψ(dFarm+distRT), p(Jdate+densTrail+survey)	9	418.3	22.16	0.00	0.17 (0.05)	0.10	(0.03)
ψ(dFarm+distRT +habitat+rtDens), p(Jdate+densTrail+survey)	12	418.3	22.21	0.00	0.28 (0.10)	0.10	(0.03)
ψ(dFarm+rtDens), p(Jdate+densTrail+survey)	9	418.3	22.23	0.00	0.20 (0.05)	0.09	(0.03)
ψ(distRT+rtDens), p(Jdate+densTrail+survey)	9	418.4	22.28	0.00	0.19 (0.05)	0.09	(0.03)
ψ(distRT+habitat+rtDens), p(Jdate+densTrail+survey)	11	418.6	22.45	0.00	0.28 (0.10)	0.09	(0.03)
ψ(dFarm+distRT+rtDens), p(Jdate+densTrail+survey)	10	418.8	22.73	0.00	0.17 (0.05)	0.10	(0.03)
ψ(dFarm+dPW+habitat+rtDens), p(Jdate+densTrail+survey)	12	419.1	23.01	0.00	0.32 (0.11)	0.09	(0.02)
ψ(dPW+distRT), p(Jdate+densTrail+survey)	9	419.5	23.44	0.00	0.18 (0.05)	0.09	(0.03)
ψ(dPW+distRT+habitat), p(Jdate+densTrail+survey)	11	419.6	23.48	0.00	0.29 (0.10)	0.10	(0.03)
ψ(dPW+habitat+rtDens), p(Jdate+densTrail+survey)	11	419.9	23.80	0.00	0.35 (0.12)	0.08	(0.02)
ψ(dFarm+dPW+rtDens), p(Jdate+densTrail+survey)	10	420.0	23.85	0.00	0.21 (0.05)	0.09	(0.02)
ψ(dPW+rtDens), p(Jdate+densTrail+survey)	9	420.0	23.91	0.00	0.23 (0.05)	0.08	(0.02)
ψ(dFarm+dPW+distRT+habitat), p(Jdate+densTrail+survey)	12	420.0	23.93	0.00	0.28 (0.11)	0.10	(0.03)
ψ(dFarm+dPW+distRT), p(Jdate+densTrail+survey)	10	420.3	24.15	0.00	0.17 (0.05)	0.10	(0.03)
ψ(dFarm+dPW+distRT+habitat+rtDens), p(Jdate+densTrail+survey)	13	420.3	24.20	0.00	0.27 (0.10)	0.10	(0.03)
ψ(dPW+distRT +rtDens), p(Jdate+densTrail+survey)	10	420.4	24.27	0.00	0.19 (0.05)	0.09	(0.03)
ψ(dPW+distRT+habitat+rtDens), p(Jdate+densTrail+survey)	12	420.4	24.33	0.00	0.29 (0.10)	0.09	(0.03)
ψ(dFarm+dPW+distRT+rtDens), p(Jdate+densTrail+survey)	11	420.6	24.47	0.00	0.17 (0.05)	0.10	(0.03)
ψ(.), p(Jdate+densTrail+survey)	7	421.7	25.61	0.00	0.24 (0.05)	0.08	(0.02)
ψ(dFarm), p(Jdate+densTrail+survey)	8	422.1	26.00	0.00	0.21 (0.05)	0.09	(0.03)
ψ(dPW), p(Jdate+densTrail+survey)	8	422.2	26.13	0.00	0.22 (0.05)	0.09	(0.03)
ψ(dPW+habitat), p(Jdate+densTrail+survey)	10	422.4	26.34	0.00	0.33 (0.10)	0.09	(0.03)
ψ(dfarm+dPW+habitat), p(Jdate+densTrail+survey)	11	423.1	27.03	0.00	0.32 (0.10)	0.10	(0.03)
ψ(dFarm+dPW), p(Jdate+densTrail+survey)	9	423.2	27.13	0.00	0.20 (0.05)	0.10	(0.03)
ψ(dFarm+habitat), p(Jdate+densTrail+survey)	10	423.3	27.22	0.00	0.30 (0.09)	0.09	(0.03)
ψ(habitat), p(Jdate+densTrail+survey)	9	423.5	27.37	0.00	0.33 (0.10)	0.08	(0.02)

dFarm: distance from de nearest farm; dPW: distance from Puerto Williams; distRT: distance from the nearest road/trail; H:H: habitat:height interaction; Jdate: Julian date; rtDens: road and trail dens