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FINE SCALE APPROACH TO PROPOSE CONSERVATION AREAS FOR THE ENDANGERED ANDEAN CAT (*Leopardus jacobita*) IN CHILEAN DRY PUNA

Tesis para optar al Grado Académico de Magíster en Areas Silvestres y Conservación de la Naturaleza.

NICOLÁS FERNANDO LAGOS SILVA

Ingeniero en Recursos Naturales Renovables

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Profesor(a) Guía	Nombre: Jaime Hernández Palma Nota: ______________________ Firma: ______________________
Profesor(a) Consejero(a)	Nombre: Pedro Cattan Ayala Nota: ______________________ Firma: ______________________
Profesor(a) Consejero(a)	Nombre: Benito González Pérez Nota: ______________________ Firma: ______________________

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Abstract

Working with rare species imposes a series of challenges. Among them, knowing its actual distribution, essential information when establishing conservation programs. Given this difficulty, the modeling of species distribution is a useful approach, since it allows to estimate the distribution of the species where it is unknown.

The Andean cat (*Leopardus jacobita*) is an extremely rare and unknown species. It distributes in the central Andes, at altitudes reaching up to 5000 masl. It is listed as Endangered by the International Union for Conservation of Nature (IUCN) and their populations are highly threatened due to habitat loss and degradation, especially in the northern part of its distribution.

Fine-scale approaches on species distribution is useful when working on landscape scale conservation programs. The present study aims to determine priority areas for the conservation of the Andean cat in the dry puna of Chile, a highly threatened area due to an increasing mining activity. The potential distribution of the Andean cat was estimated through Maxent and Random Forest modelling algorithms, using 51 points of occurrence and a set of bioclimatic and topographic variables. Additionally, the main threats to their populations were mapped through the Human Influence Index and their formal protection through protected areas.

The predictive variables with the greatest contribution in the distribution models were three related to temperature, one with precipitation, in addition to the distance to wetlands and the Topographical Position Index (TPI). The total area predicted as suitable for the Andean cat was 923.4 km^2, which showed a highly fragmented pattern. Based on the information generated by the distribution model of the Andean cat, its threats and formal protection, four priority areas were defined. This information will be useful to guide and prioritize future actions towards the conservation of the species in the dry puna of Chile.

Resumen

El trabajo con especies raras impone una serie de dificultades y desafíos. Entre ellos, la obtención de información primaria acerca de su distribución. Esta es una información clave al momento de establecer programas de conservación. Ante esta dificultad, el modelamiento de distribución de especies resulta de gran utilidad, ya que permite estimar la distribución de las especies en donde ésta se desconoce.

El gato andino (*Leopardus jacobita*) es un felino extremadamente raro y desconocido. Se encuentra catalogado como En Peligro de Extinción por la Unión Internacional para la Conservación de la Naturaleza (UICN). Se distribuye en los Andes centrales, en altitudes que llegan hasta los 5000 msnm. Sus poblaciones se encuentran altamente amenazadas por la pérdida y degradación de su hábitat, en especial en la porción norte de su distribución.

Información a escala fina acerca de la distribución de especies resulta útil al momento de trabajar en programas de conservación a escala de paisaje. El presente estudio tiene como objetivo la determinación de áreas prioritarias para la conservación del gato andino en la puna seca de Chile, un área altamente amenazada por actividad minera. Para esto, se estimó la distribución potencial del gato andino. Esta se realizó a través de los algoritmos Maxent y Random Forest, utilizando 51 puntos de ocurrencia y un set de variables bioclimáticas y topográficas. Adicionalmente se mapearon las principales amenazas a sus poblaciones mediante el Índice de Influencia Humana y su protección formal a través de áreas protegidas.

Las variables que más aportaron en los modelos de distribución fueron tres relacionadas con la temperatura, una con la precipitación, además de la distancia a humedales y el Índice de Posición Topográfica (TPI). El área total predicha como apta para el gato andino fue de 923.4 km^2, la cual mostró un patrón altamente fragmentado. En base a la información generada por el modelo de distribución del gato andino, sus amenazas y protección formal, se definieron cuatro áreas

prioritarias. Esta información permitirá guiar y priorizar acciones hacia la conservación de la especie en la puna seca de Chile.

Introduction

Rare species are of special concern in conservation biology. This species are often more prone to extinction than common species (Dobson et al., 1995; Yu & Dobson, 2000), and thus being of special interest in conservation and management programs around the world. Rarity also presents challenges to detect and estimate abundance or distribution this kind of species (McDonald, 2004), a crucial aspect when developing a conservation strategy. Occurrence records of rare species are usually very scarce, spatially biased or inexistent for some unsurveyed areas (Engler et al, 2004). Moreover, the lack of knowledge of basic information entails a difficulty for management of conservation programs, even for relatively well studied species (Anderson & Martínez-Meyer, 2004). On this regard, the estimation of the potential distribution through modelling approaches becomes a useful tool not only to fulfill existing gaps of information of species distribution, but also for conservation purposes (Marcer et al, 2013).

Species Distribution Models (SDM) seeks to characterize the distribution of species through the combination of the ecology, geography and statistics, allowing to predict the occurrence of species in unsurveyed areas (Elith & Leathwick, 2009; Franklin, 2009). Species Distribution Models associate environmental predictors with presence/absence observations and develop rules who are used to classify new observations where the values of the predictors, but not the response, are known (Franklin, 2009). The applications of SDM are diverse, including ecological dynamics, ecological restoration, biogeography, species reintroduction, impact of exotic species, effects of climate change on ecosystems, design of natural reserves or the elaboration of conservation programs (Guisan & Thuiller, 2005; Franklin, 2009; Guisan et al, 2013; Liu et al, 2013; Lyet et al, 2013), resulting useful for rare species or with conservation problems, and as a tool to prioritize and develop conservation actions (Anderson & Martínez-Meyer, 2004; Hirzel et al, 2006).

The Andean cat (*Leopardus jacobita*) is among the least known felids in the world, one of the only six cat species considered Endangered by the IUCN, and the

Americas' most threatened felid (Nowell & Jackson, 1996; Andean Cat Alliance, 2011; Villalba et al, 2016). It's an extremely rare species, occurring at low densities (Reppucci et al, 2011; Huaranca et al, 2013) who inhabits the high-altitude deserts of the central Andes and southern Andean Steppe, up to 5000 masl., at environments with heterogeneous geomorphology and extreme weather conditions (Villalba et al, 2016). It prefer areas with presence of Andean bogs, called 'vegas' or 'bofedales' and steep-rocky formations, habitats which are naturally fragmented in the landscape (Marino et al, 2010; Villalba et al, 2016). Besides its ecological importance, the Andean cat is considered a sacred cat by the Andean cultures, being part of their traditions and religious beliefs, related with the fertility and prosperity in the agricultural and livestock production (Grebe, 1989; Andean Cat Alliance, 2011). This symbolic relevance gives this felid an additional value for its conservation, as a mainstay within the rituals and traditions of the Andean cultures.

Besides, Andean cat populations are highly threatened. Habitat loss and degradation are of increasing concern in most areas where the Andean cat is present, mainly due to the expansion of agricultural frontier, inadequate livestock raising practices and water extraction for the mining industry (Andean Cat Alliance, 2011; Villalba et al, 2016). Despite this, no study have addressed their effects in Andean cat populations (Zanin et al, 2014). Furthermore, for the northern area of the distribution of the species, in the Andean plateau, it's expected a decrease on wetlands area due to climate change (IEB, CASEB, CCG-UC–CONAMA, 2010), what could increase habitat loss in the future. Assessing the impact of human activities on ecosystems is a keystone in conservation planning, helping to prioritize areas where urgent actions are needed (Brooks et al, 2006). Lack of spatial information of those impacts hamper the development of strategies at a landscape level. Faced with this problem, SDM are useful to evaluate the consequences of habitat loss in local fauna, and to plan conservation programs for its long term conservation, especially for felids, taxa particularly sensitive to disturbances (Miller et al, 2001; Zanin et al, 2014). Since most threats occur at a local scale, a fine scale approach is needed to correctly apply conservation or management programs.

Spatial scale is relevant when developing a SDM. It will depend on the data availability and on the objective of the study (Elith & Leathwick, 2009). Large scale studies (i.e. 1x1 km cells or more) are generally developed to recognize global patterns in species distributions. However, if a landscape scale approach is needed, such as for the implementation or management of protected areas or selecting sites for species reintroduction, finer scales should be used (Franklin, 2009). At this time, no studies have addressed the spatial relationship of the Andean cat to its habitat at a fine scale (Marino et al, 2011). This kind of approach can provide relevant information for regional biodiversity conservation planning, and it is particularly useful for conservation purposes (VanDerWal et al, 2009; Lyet et al, 2013). On this study we applied a fine scale approach to determine the distribution and define conservation areas for the Andean cat in the dry puna of northern Chile, a zone of interest for the conservation of this species, since it contains the highest amount of occurrence records of the species, nevertheless a highly threatened area due to mining activities (Villalba et al, 2016).

The main objectives of this project are i) to recognize the factors affecting the Andean cat distribution in the dry puna of Chile and predict its potential distribution, ii) to evaluate the actual protected status in the area and their threats, and iii) propose priority areas for the conservation of the species.

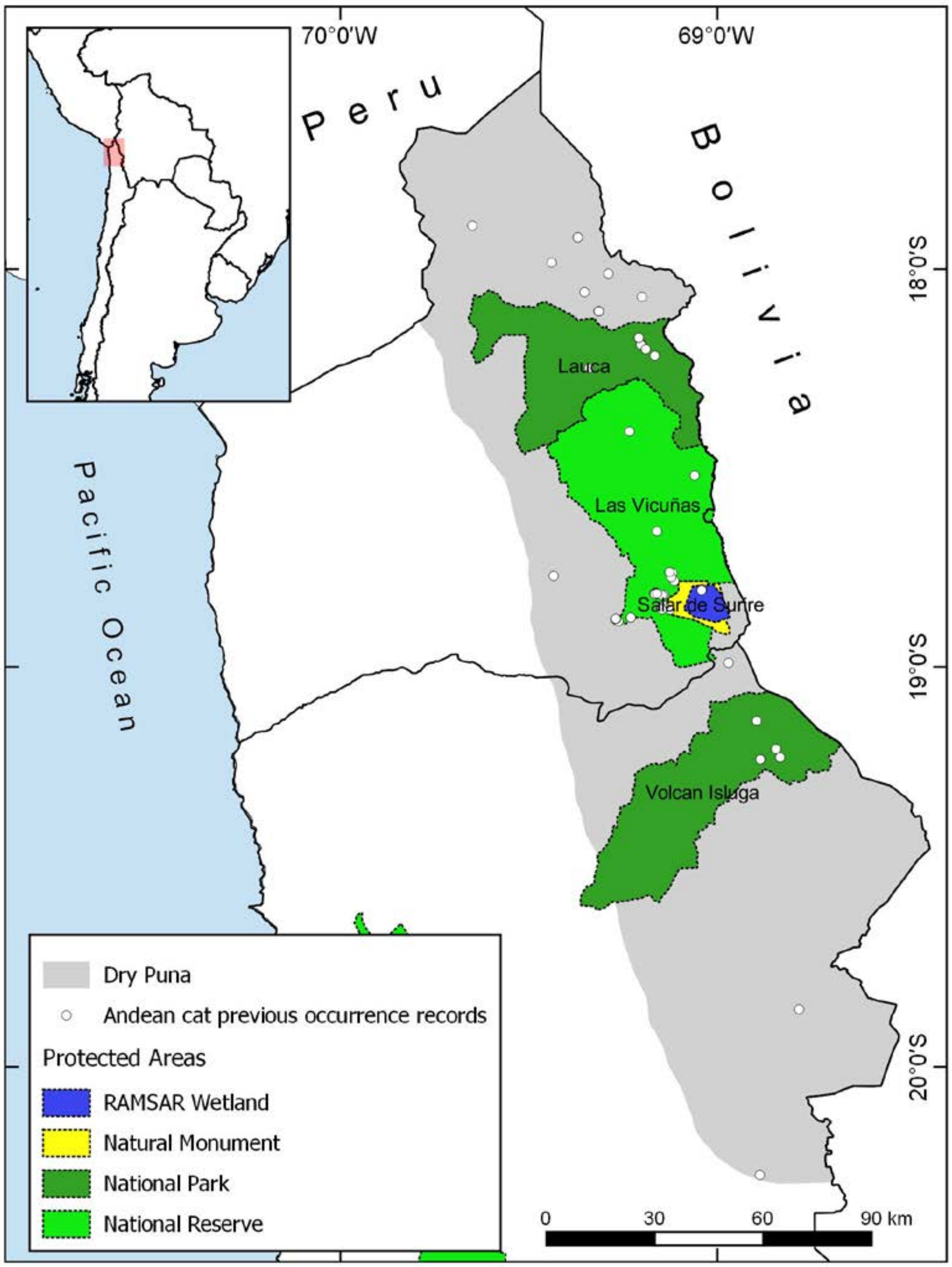
Methodology

Study Area

The study was conducted in the dry puna of northern Chile (Cabrera, 1968), in altitudes ranging from 3500 to 5200 masl, geographically in the region of Arica and Parinacota and the north of the region of Tarapacá (Figure 1). This area corresponds to the northern distribution of the Andean cat in Chile. Acording to Cossíos et al, (2012) the populations of this area corresponds to a genetically structured group, shared with neighboring zones of Bolivia and Peru, who should be considered as a single management unit.

The dry puna is characterized by a mean annual precipitation between 100-400 mm (Cabrera, 1968), and the presence of rivers, lakes and salt flats. It presents a cold climate, showing an annual temperature average of 2°C, with ranges over 20° C between day and night, and rainfall of tropical origin concentrated in the austral summer (Cabrera & Willink, 1973; Di Castri & Hajek, 1976; Garreaud et al. 2003). Ecologically, the study site is located on the high Andean steppe, specifically in the sub-region of the Altiplano and Puna (Gajardo, 1994). Typical vegetation communities are composed by wild grasses (*Stipa sp*. and *Festuca sp.*) and evergreen shrubs (*Parastrephia sp.* and *Baccharis sp.*). Above 4000 masl., cushion shape plant species called ‘llareta’ (*Azorella compacta*) grows associated to rocky slopes; and between 4200 to 5200 are the highest forests of the world, composed by the ‘queñoa’ (*Polylepis tarapacana*). A plant community of wetland grasses called ‘bofedal’, is the typical floristic and vegetational complex in watercourses, where cushions of *Oxychloe andina* are the most relevant species (Rundel & Palma 2000; Trivelli & Valdivia, 2009). These areas, as well as the rocky outcrops, main source of shelter and food for the Andean cat, are naturally fragmented and scattered in the landscape of the Andean puna.

Figure 1. Study area



Species Distribution Modelling

Occurrence data

Primary occurrence data was obtained through the Andean Cat Alliance (AGA) database, with records spanning between 1988 to 2014. Inside the study area the database comprised 66 records, 6 of which corresponding to skin samples, 32 to DNA extracted from faecal samples, 25 of records from camera traps and 3 direct sightings. To secure no spatial autocorrelation between records and to avoid overrepresentation of local attributes, we selected only one locality per each 5x5 km cell (Marino et al, 2011), maintaining its spatial independence. Then, the resulting dataset comprised a total of 27 records (3 skin, 4 faecal DNA samples, 17 records from camera traps and 3 direct sightings).

Accounting for spatial bias in occurrence records is a recommended approach when original input data is geographically biased. This is a common issue when working with available datasets rather than from specially designed surveys (Kramer-Schadt et al, 2013; Fourcade et al, 2014; Varela et al, 2014). In this cases, the quality of the resulting model can be affected, leading to inaccurate prediction and thus misguided decisions (Dormann et al, 2007; Syfert et al, 2013; Fithian et al, 2014; Varela et al, 2014). In order to avoid spatial bias in primary occurrence data and to ensure an homogeneous sample (Engler et al, 2004; Soberon & Peterson, 2005; Phillips et al, 2009; Lobo et al, 2010; Acevedo et al, 2016), we randomly selected 100 sites in under-represented regions and areas never sampled before (Phillips et al, 2009). Sites were separated by at least 5 km between them and between any occurrence point or previously surveyed site (Napolitano et al, 2008; Marino et al, 2011). This allowed us to reduce the spatial bias of occurrence records and increase it representativeness throughout the study area. Within each site we considered a radius of 1 km where we deployed a camera trap with passive infrared sensor (model Bushnell TrophyCam IR). The site where the camera was installed was selected in order to maximize its probability of capture (McDonald, 2004), preferring locations with indirect presence signs of the species (i.e. tracks, latrines and/or presence of its main prey, *Lagidium spp.*

(Walker et al, 2007; Napolitano et al 2008)) but properly representing the habitat heterogeneity of the study area. Cameras were lured with bobcat pee and other cat specific scents or glands. They were deployed in four different campaigns, between February and December 2015, completing a total of 96 sites. Each camera worked for at least 60 trap/night and programed to operate continuously, taking 3 pictures per event and with an interval of 10 seconds between events. In the same 1 km radius we extensively searched for latrines in the nearest rocky outcrop. One and occasionally two faecal samples were collected from each site, selecting always the freshest scat in latrines. Samples were stored in the field in 50 ml Falcon tubes filled with absolute Ethanol and brought to the Laboratory of Evolutionary Biology at P. Universidad Católica de Chile for species identification. Species identification were performed through PCR (Polymerase Chain Reaction), using mitochondrial fragments: ATP-8, 16S and two portions of the NADH-5, using primers and conditions published in Johnson et al. 1998. These mtDNA fragments are broadly used in felid studies because they are polymorphic, well described, and because it there exists a good collection of references sequences for both species (Johnson et al, 1998; Cossios et al, 2012; Napolitano et al, 2008). We repeated a 15% of PCR amplifications of faecal samples for each gene fragment to ensure repeatability of species identification. DNA was extracted from epithelial rectal cells impregnated on faeces, using a specific kit (QIAamp DNA Stool Mini Kit, QIAGEN, Valencia, California), following the manufacturer's suggested protocol (Cossios et al, 2012; Napolitano et al, 2008).

Predictor variables

We selected potential predictors including both broad scale climatic and finer scale topographic variables (Table 1). This allowed us to make inferences at both coarse and finer (landscape) scale (Franklin, 2009). All layers were rescaled to a 30 m resolution using QGIS 2.14.7. To identify and work only with the variables most closely associated with occurrence localities, we excluded least significant variables in a stepwise fashion. We preliminarily fitted initial Maxent and Random Forest models considering all predictors, using the R package Dismo (Hijmans &

Elith, 2013). Model parameters were the same as used in section 2.2.3. Ten iterations per modelling method were made. Then, we explored variable contribution for each modelling method, excluding the variables with the lowest scores (i.e. less than 2%). Between redundant variables (i.e. with a Pearson coefficient >0.9) those with higher contribution were preferred. When any ecologically relevant variable was suggested to be excluded through this procedure, we preferred to keep it for the further analyses (Dormann et al, 2013). This procedure was repeated until all remaining variables were statistically or ecologically relevant.

Table 1: Predictor variables considered for the initial selection

Predictor variables	Description	Spatial resolution	Source
Bioclimatic variables	Nineteen bioclimatic variables derived from a dataset of monthly climatic variables (1950-2000)	1 km	Pliscoff *et al.*, 2014
High Andean Wetlands	Detailed information of the high Andean wetlands of northern Chile	vector	SITHA
DEM	Digital Elevation Model from ALOS-1 PALSAR Global Radar Imagery, 2006-2011	12.5 m	Alaska Satellite Facility
TPI	Derived from the DEM from SAGA toolbox in QGIS 2.14.3	12.5 m	Alaska Satellite Facility
Slope	Derived from the DEM from SAGA toolbox in QGIS 2.14.3	12.5 m	Alaska Satellite Facility
Land Cover Chile 2014	Land cover for Chile year 2014	30 m	Zhao *et al.*, 2016
NDVI	MODIS Normalized Difference Vegetation Index	1 km	MODIS Vegetation-Index (VI)
EVI	MODIS Enhanced Vegetation Index	1 km	MODIS Vegetation-Index (VI)

Modelling approach

Many modelling methods are widely used in the literature to build species distribution models (Segurado et al, 2004; Elith et al. 2006; Elith & Leathwick, 2009; Franklin, 2009; Aguirre-Gutiérrez et al, 2013; Qiao et al, 2015). Among them, Maxent and Random Forest has proved to be two of the best performing methods (Elith et al, 2006; Elith & Graham, 2009; Liu et al, 2013). Maximum entropy or Maxent is a machine learning method who seeks to estimate a probability distribution closest to uniform, subject to known constraints. In the case of SDM, the constraints are that the expected value of predictor variables should match its empirical average (Phillips et al, 2006). Random forest is also a machine learning method, who consists on a large number of classification trees, built with randomized subset of predictors, chosen to find the best split at each node (Breiman, 2001). Trees are grown without pruning and resulting predictions are averaged (Franklin, 2009). We used R package Dismo (Hijmans & Elith, 2013) for both algorithms, following the settings proposed by the authors. We partitioned the occurrence locations at random in two subsamples, 80% of locations were used as training dataset and the remaining 20% to test the resulting models (Marino et al, 2011). Random Forest models were constructed growing 1000 trees per iteration. We randomly chose 1000 pseudoabsences throughout the study area (Wisz & Guisan, 2009; Lobo & Tognelli, 2011), but excluding sites with known records (Liu et al,. 2013). To avoiding them to coincide with occurrence locations, a radius of 1 km from each occurrence location were excluded. This number of pseudoabsences avoid overprediction (Lobo & Tognelli, 2011), useful when working with reserve design and conservation purposes and with rare or endangered species (Jiménez-Valverde & Lobo, 2006; Lobo & Tognelli, 2011), aiming to a correct classification of absences but increasing misclassification of presences (Lobo & Tognelli, 2011). To obtain a robust estimate we ran 100 iterations per modelling algorithm and combined them in one unique model by weighting the area under the curve (AUC) of the receiver operating characteristic (ROC) plot (Hijmans & Elith, 2013; Aguirre-Gutiérrez et al, 2013).

Model threshold and validation

The AUC is one of the most commonly used coefficients to measure model performance (Elith et al, 2006; Hernandez et al, 2006; Freeman & Moisen, 2008). However, some authors have criticized the use of AUC, mainly because it doesn't take into account the data prevalence and it equally weights commission and omission errors (Austin, 2007; Lobo et al, 2008; Jiménez-Valverde, 2012). Converting the map to a binary surface using a threshold is useful to perform future analyses as well as for evaluating model prediction reliability (Jiménez-Valverde & Lobo, 2007). A threshold dependent measure has the advantage of providing more information of model performance than just the AUC (Jiménez-Valverde, 2014). Since there are many thresholds cut-offs available, it should be chosen considering the intended use of the SDM. When the objective of the study is to identify conservation areas or reserve design, maximizing specificity or minimizing commission errors (predicting suitable habitat where it is not suitable) is preferred, so the model would predict only in areas where the species is highly likely to be present, avoiding areas with low probability of occurrence (Papeş & Gaubert, 2007; Marini et al, 2009; Barbet-Massin et al, 2012; Liu et al, 2016). For this study, as we're not working with real absences and considering that only a percentage of the pseudoabsences would correspond to real absences, we decided to apply a value for specificity of 0.6, this means that we accept to misclassify up to a 40% of the pseudoabsences as present.

Discrimination power of the resulting binary map was measured by Sensitivity (Se), which measures the probability of the model to correctly predict a species presence at a site, Specificity (Sp), which measures the probability to correctly predict an absence, Overall Accuracy (OA), which is the probability that a site (either presence or absence) is correctly predicted, and Cohen's kappa, who corrects the OA by the accuracy expected to occur by chance (Franklin, 2009; Liu et al, 2011; Jiménez-Valverde, 2014).

Human Influence Index

Selection of threats datasets and assignment of influence scores

To define the influence of anthropogenic impacts on Andean cat populations, we mapped the Human Influence Index (HII) throughout the study area, based on the approach of Sanderson et al. (2002). Considering the threats affecting Andean cat populations (Andean Cat Alliance 2011) and available layers, we selected datasets who represent four categories of human influence who could directly or indirectly affect Andean cat populations: (a) human settlement: urban and rural areas; (b) human access: roads and vehicle trails and (c) human land cover change: agriculture and mining operations.

Data layers were obtained from different sources (Table 2), rasterized and rescaled to a spatial resolution of 30 m using the software QGIS Desktop 2.14.7. Following the methodology of Sanderson et al (2002), influence scores (described below) were assigned to each dataset regarding their contribution to the human impact on Andean cat populations, on a scale ranging from 0 (no impact) to 10 (high impact). Scores were based on previous studies and on expert opinion.

Table 2: Threat dataset used to calculate Human Influence Index

Feature	Source
Human settlements	
Global Urban Footprint (GUF)	Esch *et al*, 2012, 2013
Human access	
Chile Road Network	Military Geographic Institute
Human land use change	
Land Cover Chile 2014	Zhao *et al*., 2016
Mining operations	Mining Concessions Cadaster - SERNAGEOMIN

Human settlements: rural and urban areas

Human dwellings are directly related with environmental pressure. Such as other felid species, the Andean cat is expected to avoid human presence, preferring areas located away from human settlements. For the Andean cat, the human presence in settlements implies not only direct habitat disturbance but also pressure in surrounding areas due to human activities (Andean Cat Alliance, 2011). Spatially explicit information about population density, useful for our analyses, are not available for Chile, so we used an alternative approach. To map the influence of human settlements and urban areas we used the GUF (Global Urban Footprint) dataset (Esch et al, 2012; Esch et al, 2013). The GUF uses the global coverage of TerraSAR-X and TanDEM-X data to classify urban structures. The 12 m resolution of the GUF allowed us to recognize small villages, common throughout the study area. Approaches to assign scores in literature require population density, so in this case scores were based on expert opinion. Consultation was done to 20 active members of the Andean Cat Alliance, who assigned HI values for different buffer distance from local settlements and urban areas.

Human access: roads and vehicular trails

The existence of roads and tracks throughout the study area implies access to zones that otherwise would have almost no human impact. Roads were classified in three categories which differed in their vehicular traffic and therefore their ecological impact: paved roads included freeways and highways, secondary non-paved roads and vehicular trails. Scores were assigned to different buffer distances from each class of road based on available literature (Forman, 2000; Dickson & Beier, 2002; Woolmer et al, 2008; Poessel et al, 2014).

Human land cover change: agriculture and mining operations

We considered as land cover change, anthropogenic activities who involves any kind of land transformation. Throughout our study area, those activities include agriculture and mining operations. Two different datasets were used to map them: for agriculture we used a land cover layer of Chile (Zhao et al, 2016) and for mining operations the Exploitation Mining Concessions and Mining Operations Cadaster (SERNAGEOMIN, 2017). Mining operations include mines currently in operation. Exploitation Mining Concessions corresponds to areas where are no current mining activity, but they're asked for it exploitation in the future. Scores were based on the work of Woolmer et al (2008), considering degree and permanence of land transformation. For mining operations, we considered two approaches: for each mining operation we assigned a HI score based on Woolmer et al (2008). As Mining Concession areas indicates no actual but potential impact in the future, we assigned them lower score than mining operations. For agriculture our score was based on Woolmer et al (2008).

Sum and normalization of scores

Human Influence scores for each dataset were summed and normalized to scale their range from 0 to 10, creating the Human Influence Index (HII) throughout the study area.

Proposal of conservation areas for the Andean cat

Based on both Andean cat distribution model and HII layers we selected priority areas for the species conservation throughout the study area. An additional layer of the protected areas (IUCN & UNEP-WCMC, 2017) was considered in the analysis. Sites were selected visually, giving priority to those areas with high degree of threat, high level of habitat suitability for the Andean cat and without formal protection. Preference was given also to well-connected areas of high habitat suitability.

Results

Species Distribution Model

Occurrence data and selection of predictor variables

Of the 96 cameras deployed on the field, two had problems with SD card and other 10 kept working for less than 60 consecutive nights. In total, cameras worked during 6255 trap/nights and recorded Andean cat presence at 18 different sites (19.1%). A total of 110 faecal samples were collected. Of them, we could properly extract and amplify DNA to 99, ten of which (9.9 %) corresponded to Andean cat. If

Andean cat presence was recorded at the same site by both methodologies, only one record was considered. Finally, 24 occurrence records were added to the original dataset, totaling 51 occurrence points, used to build the model.

The selection of predictor variables led to a combination of 11 variables, used to build the final models. Four bioclimatic variables related with temperature and two related with precipitation were selected, as well as elevation, distance to wetlands, topographic position index (TPI), land cover and slope (Table 3). In cases when correlated variables had high contribution with any of the two methods we decided to retain them, giving priority to their relevance to the performance of the modelling approach. Of selected variables, the ones who showed higher contribution by either of the two modelling approaches where mean temperature of driest and coldest quarter, mean diurnal temperature range, distance to wetlands and TPI.

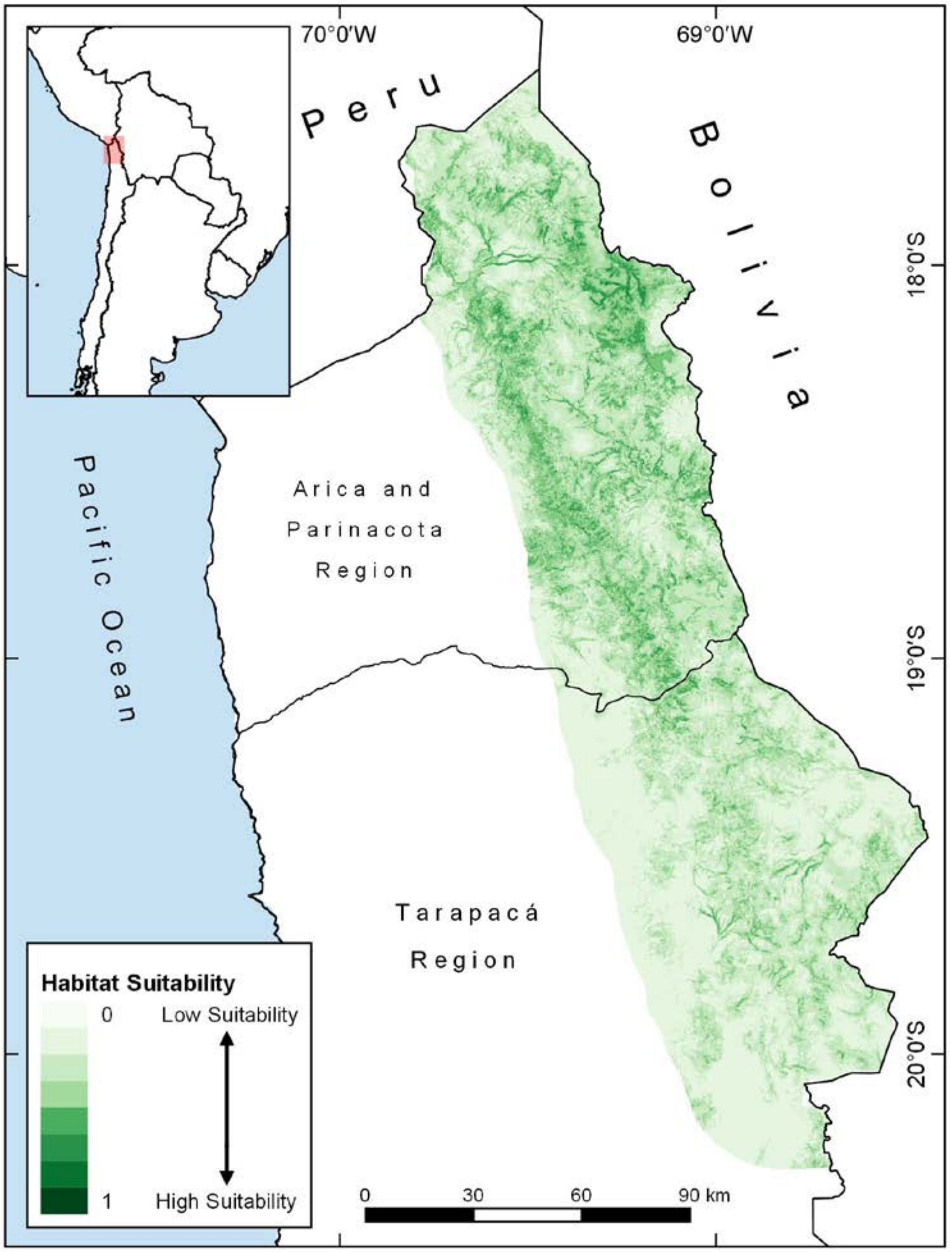
Table 3: Selected dataset used in final modelling approach. Values shown correspond to the mean value for the 100 iterations and in () the standard deviation. Highest variable contribution for each modelling approach are shown in bold.

	Variable contribution (Maxent)	Variable contribution (Random Forest)
Mean Diurnal Temperature Range	**13.96 (4.3)**	2.87 (0.3)
Max Temperature of Warmest Month	12.15 (1.1)	3.86 (0.4)
Mean Temperature of Driest Quarter	**16.68 (0.9)**	2.75 (0.2)
Mean Temperature of Coldest Quarter	**14.68 (1.6)**	2.83 (0.2)
Precipitation of Wettest Month	12.38 (1.1)	3.63 (0.2)
Precipitation of Wettest Quarter	**12.85 (1.6)**	3.46 (0.2)
Elevation	11.07 (1.1)	2.98 (0.2)
Distance to wetlands	5.13 (3.3)	**5.64 (0.7)**
TPI	5.7 (6.6)	**5.11 (0.5)**
Slope	8.68 (2.7)	3.48 (0.3)

Model selection, threshold and validation

Both modelling approaches showed good fit to the data and no differences in their performance (AUC: Maxent = 0.93±0.02; Random Forest = 0.92±0.03). Predictions of both modelling approaches were similar but with a slight difference: Maxent showed a less conservative approach and predicting higher suitability in the puna belt, on the northwest of our study area. From the 100 iterations, models were averaged by its AUC and then combined in a single final model. Threshold calculated for a fixed specificity of 0.6 yielded a value of 0.48, used to convert the continuous suitability map into a binary one. Accuracy of this final model was high, showing a high OA (0.97) and kappa (0.66). Sensitivity was 0.63 and specificity 0.99. The total area predicted as suitable by the model covered 923.4 km^2, mostly concentrated in the Arica and Parinacota Region, and including areas above 3.200 masl in the high Andes and the puna belt (Figure 2). The suitable areas showed a highly fragmented pattern with more connected areas associated to larger ravines and Andean bogs, whereas non suitable areas where related mostly to plain areas or ‘pampas’.

Figure 2: Projected potential distribution of the Andean cat (*Leopardus jacobita*) in Chilean dry puna.



Human Influence Index

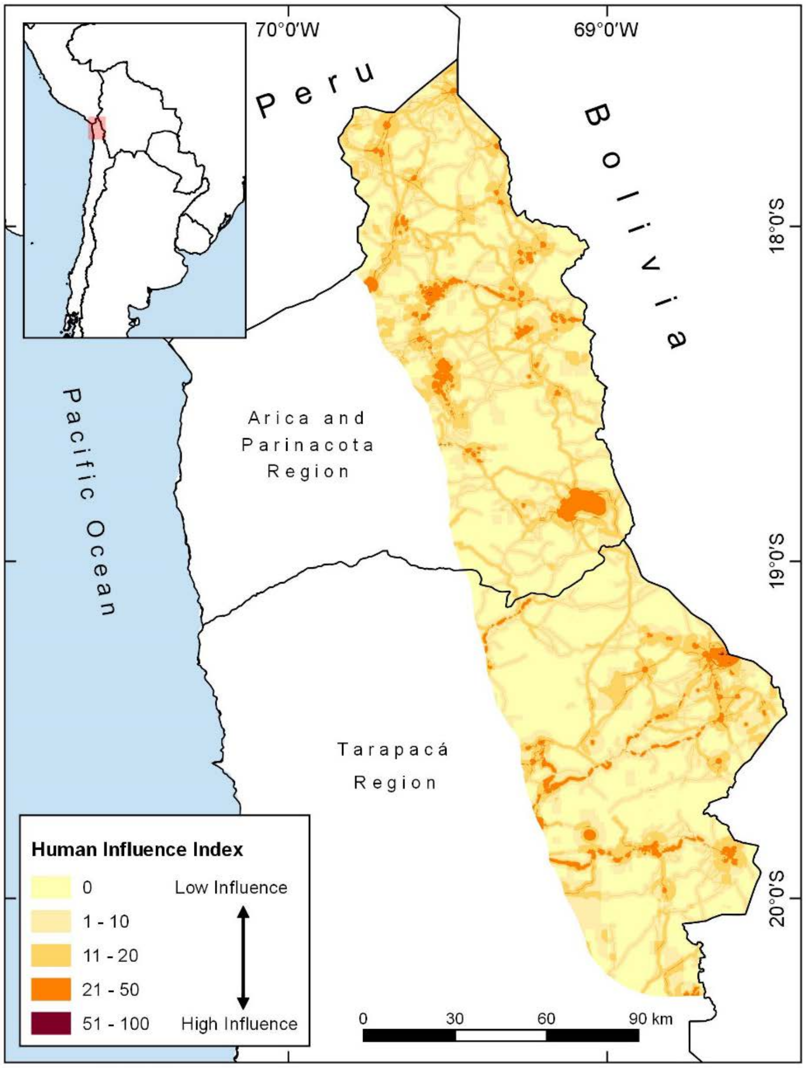
Scores used to build the HII layer are shown in Table 4. The HII map showed a different degree of human influence across the study area. Areas with higher HII where related with the presence of mining operations and human settlements, followed by areas with presence of roads. Areas with very low or no degree of human transformation (HII ≤ 10) covers the 73.5% of the study area, accounting for its low degree of anthropogenic impacts. Nevertheless, the spatial configuration of those areas shows a high amount of landscape fragmentation, which are separated by zones with medium or high degree of human transformation (Figure 3).

Table 4: Human Influence scores for the dataset

		0 - 100 m	100 - 500 m	500 - 1000 m	1000 - 2000 m	2000 - 4000 m
Human Settlements						
	Urban areas	10	8	6	4	2
	Rural areas	8	6	4	2	2
Roads						
	Paved roads	8	6	4	2	0
	Non-paved roads	5	3	2	0	0
	Vehicular trails	3	2	1	0	0
		0 - 500 m	500 – 1500 m	1500 – 2500 m	2500 – 5000 m	
Human Land Cover Change						
	Mining operations	9	7	5	2	
	Exploitation Mining Concessions	2 (*)				
	Agriculture	6 (*)				

(*) No buffer considered

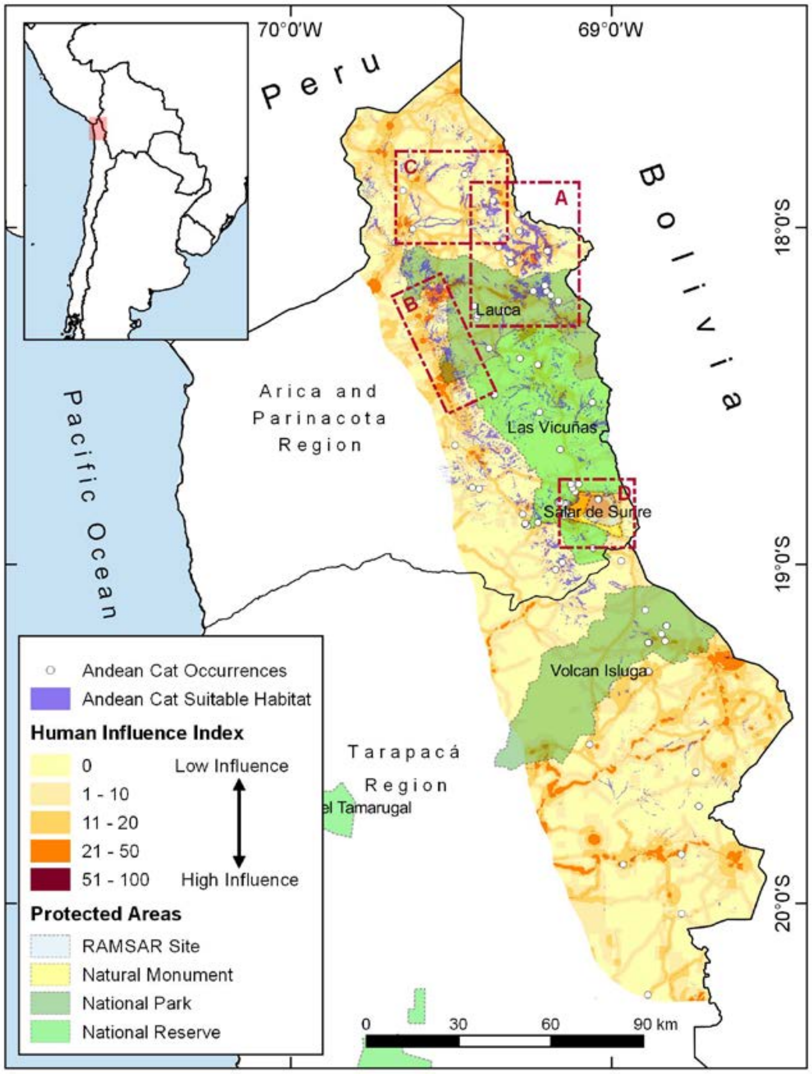
Figure 3: Human Influence Index of the Chilean dry puna.



Proposal of conservation areas for the Andean cat

Based on Andean cat habitat suitability, human influence index and actual protected areas, four geographic areas were selected as priorities to conduct programs or actions towards Andean cat conservation (Figure 4).

Figure 4: Priority areas for the Andean cat conservation in Chilean dry puna.



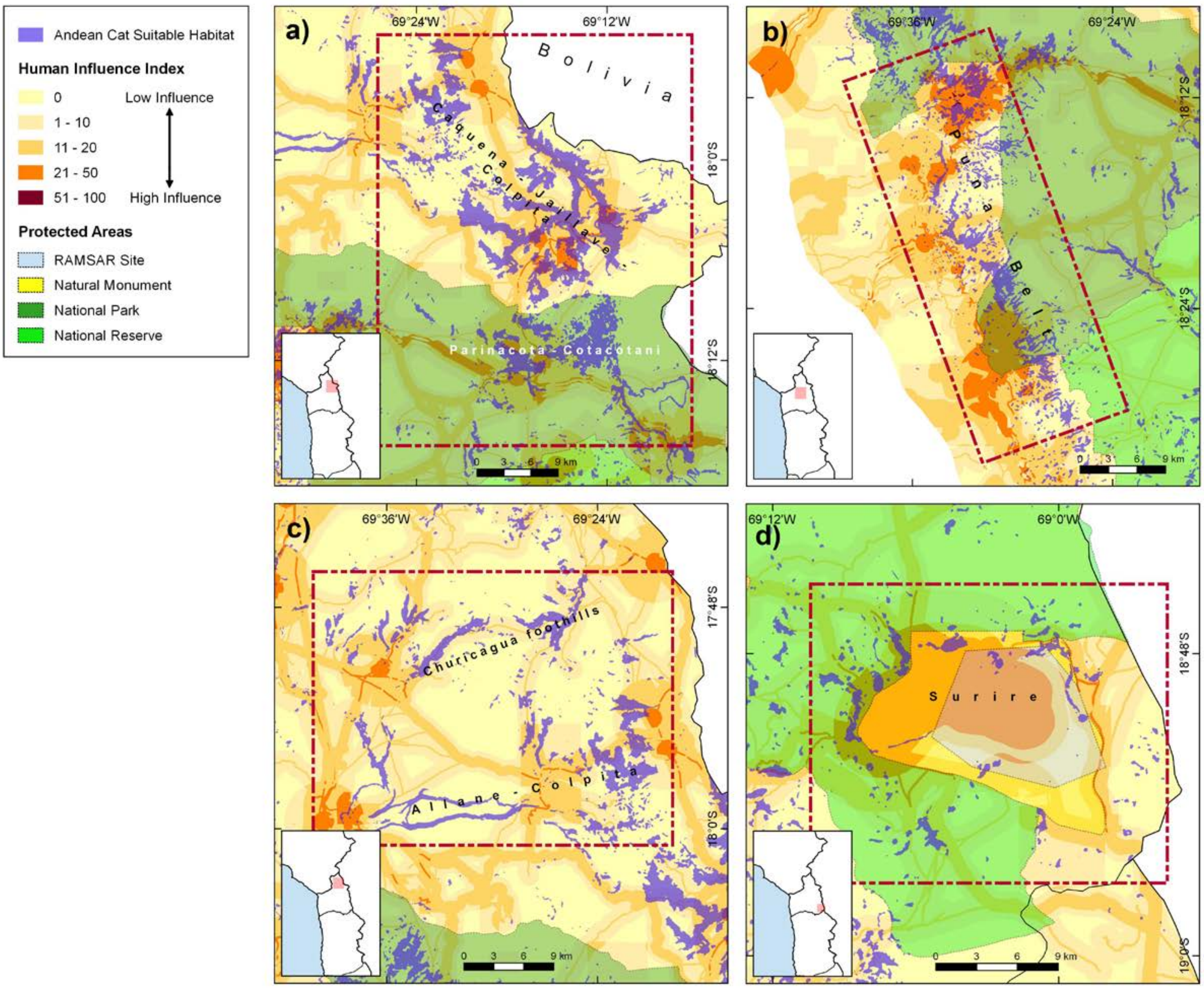
Area A: Comprises two major zones, both located in the Altiplano. The zone of Parinacota and Cotacotani, located at the south of this area (Figure 5a), is a relatively flat area with presence of small hills and rocky hillsides that embrace the Andean bog of Parinacota and the lagoons of Cotacotani. The high geographic complexity of this zone, with well-connected rocky formations and water sources, makes it an important habitat to maintain Andean cat populations. In fact, a total of 16 Andean cat records have been registered in this zone, which is formally protected as part of the Lauca National Park. Connected at the north of this zone and without formal protection is located the Caquena – Jaillave – Colpita complex. This is a zone of well-connected ravines with rocky slopes and Andean bogs, converting it in a network of suitable habitat for the Andean cat. Both zones have medium to high human influence, due to the presence of human settlements and an exploitation mining concession which, although is not actually a threat, it could be in the near future if a mining operation is established. Both areas cover an area of approximately 238 km^2. According to the above, we consider this area as the most prioritary in the Chilean dry puna to take conservation actions for the Andean cat.

Area B: This area is located in the puna belt of the Arica and Parinacota Region (Figure 5b). It is characterized by its rugged terrain, formed by several ravines in east-west direction. The result of the habitat suitability map shows a highly fragmented habitat, with suitable habitat covering approximately 96 km^2 of surface. This area is highly influenced by mining activities; one active mining operation and several exploitation concessions are present in this zone, threatening this ecosystem. No occurrence records of Andean cat were registered in this area, but the final model showed high habitat suitability for the species, so validation through field surveys is recommended.

Area C: Although this zone presents no major threats, it’s an area of interest because it encompasses suitable areas with a low level of fragmentation. Those areas correspond to deep ravines of Allane and Colpita, and other of medium size located at the foothills of Churicagua mountain (Figure 5c). This area covers a total surface of 111 km^2 of highly suitable habitat, who could be used as natural corridors between Andean cat populations in the Altiplano (Area A) and the puna belt (Area B).

Area D: The surroundings of Surire salt flat concentrates the highest amount of Andean cat occurrence records of the study area (24 records). The scattered pattern of the habitat suitability map, covering a small area, of nearly 29 km^2 of highly suitable habitat, reflects the presence of fragmented rocky outcrops, where the Andean cat records were obtained. The only anthropogenic pressure to this area is the presence of a mining operation, who extracts borax from the Surire salt flat, actually a Chilean Natural Monument and RAMSAR site, threatening the Andean cat populations and local biodiversity (Figure 5d).

Figure 5: Prioritization of four areas for the Andean cat conservation in Chilean dry puna: Cotacotani - Caquena (a), Puna belt (b), Churicagua – Allane (c), and Surire (d).



Discussion

This study presents a fine scale approach to define conservation areas for the Andean cat, an extremely rare and threatened species. This kind of approaches are uncommon but useful to identify critical habitat and design fine-scale conservation strategies and programs (Lyet et al, 2013; Peterman et al, 2013). In our study, this approach was combined with a spatially explicit threat analysis in order to define and prioritize areas for the conservation of the Andean cat in the dry puna of Chile.

This study provided useful information about environmental requirements for Andean cat's distribution. Bioclimatic variables accounting for the main climatic characteristics in the dry puna were selected by Maxent model (Table 4): precipitation concentrated in the austral summer season, especially on the western side of the Altiplano, our study area, accompanied by higher temperatures, and a strong difference of temperature between day and night (Garreaud et al, 2003; Seth et al, 2013). On the other hand, Random Forest showed greater importance to predictors related with topographic variables (Table 4), related to key variables for Andean cat at a landscape scale: the presence of rocky formations, important not only for the Andean cat but also for its main prey, the mountain vizcacha (Walker et al, 2000; Andean Cat Alliance, 2011; Villalba et al, 2016); and water availability, related with the presence of Andean bogs, known as 'vegas' or 'bofedales' (Cortés et al, 2002; Marino et al, 2010; Cuyckens et al, 2015). Although elevation has proven to be a key factor in Andean cat distribution (Marino et al, 2011), in our final models wasn't among the most important predictors. Elevation is correlated with temperature, so bioclimatic predictors associated with this variable may be masking the effect of elevation alone. Discrepancies among both modelling techniques in variable contribution could be due to their different algorithms in selecting variables and accounting them in model construction (Franklin, 2009). However, final predictions of both modelling methods were similar and showed high predictive value. Our results confirmed that the Andean cat is a highly specialist species, preferring areas with rocky formations and near water sources (Marino et al, 2010), habitat of its main prey.

All values of model performance calculated were high for both modeling approaches. Area under the curve (AUC) of ensemble Random Forest and Maxent model had a high value (0.93). Since AUC is not recommended by several authors (Austin, 2007; Lobo et al, 2008; Jiménez-Valverde, 2012), four alternative accuracy indexes were calculated from binary suitability map (Liu et al, 2011). Values for Specificity (0.99), Overall Accuracy (0.97) and Kappa (0.66), were high, indicating a good model performance. On the other hand, sensitivity value (0.63) was low. This was to be expected because we chose an stringent threshold, in order to be secure that the area selected is where the species is likely to be present (Wilson et al. 2005; Barbet-Massin et al, 2012). This method is useful when designing reserves or sites for species conservation, ensuring that resources and effort will be allocated in areas where is reasonably sure to find the species (Wilson et al, 2005). The combination of alternative indexes to assess model performance is useful because it overcome the deficiencies of the different accuracy measurement approaches, being more informative than using a single measure alone. Besides, its results must be interpreted in the context of the objectives of the study and the application of the model.

Final binary map showed a fragmented distribution of critical suitable habitat for the Andean cat, which accounts for the habitat specialty of the Andean cat. Rocky outcrops are the preferred habitat for the species which, consistent with our results, are naturally fragmented (Marino et al, 2010; Marino et al, 2011; Villalba et al, 2016). Besides, Andean bogs are frequently surrounded by rocky formations, sometimes covering vast areas along ravines, who could be used as natural corridors not only for the Andean cat but for other species. Extensive areas of plains, called ‘pampas’ are not preferential for the species, but could be used for dispersion between patches. Further studies focused on the utilization of this matrix of unsuitable habitat by the Andean cat are required in order to identify if they’re being used between patches of suitable habitat.

Main threats for the Andean cat includes the presence of human settlements and mining operations, which are well distributed throughout the study area (Figure 3).

The threat of this activity entails not only it direct impact by habitat destruction and modification, but also by water extraction, a scarce resource throughout Andean cat distribution. Mining is a growing industry in Chile, which is evidenced in the extent of granted exploration and exploitation concessions (SERNAGEOMIN, 2017), so is expected that this threat may be increased in the near future. It demand has caused the drain of water sources in the Altiplano, including Andean bogs and salt flats, a key resource not only for Andean cat and biodiversity but also for local communities (Bolados, 2014; Morales & Azócar, 2015). Moreover, tropical Andes has showed on the last decades an aridization trend (Carrilla et al, 2013), affecting directly to water sources and primary productivity, which could aggravate this problem in the near future.

The combined methodology of SDM and IIH maps showed to be useful to locate areas for the conservation of the Andean cat in northern Chile. Four zones were selected as priority to conduct management programs towards conservation of this species. Of those areas, we considered Area A as the most important (Figure 5a), because it has a large amount of well-connected suitable habitat (238 km^2 approx.) and has three core areas with high level of threat. Major part of this area remains unprotected, with only a section at the south included in the Lauca National Park. We strongly recommend this area, at the northeast of the park, to be included and prioritized as part of their conservation programs. This zone corresponds to Parinacota - Cotacotani lagoons, which have not only interest for Andean cat populations but also for other Andean biodiversity (Rundel & Palma, 2000; Márquez-García et al, 2009; Guerrero et al, 2015). Besides, Cotacotani lagoons serves as the source of the Lauca, the main river of the basin, turning them into a key water source for the maintenance of the ecosystem. This area is connected at the north with the Caquena – Jaillave – Colpita complex, a system of ravines with rocky outcrops and water sources, which makes the whole area a priority habitat for the Andean cat. Since restructuration of park boundaries is difficult, future conservation and management plans of the park should definitively consider this zone outside its boundaries.

Future research is needed in Area B in order to validate model predictions through field surveys. This area has a high surface of habitat suitability, but have no Andean cat occurrence records. Besides, this area is highly threatened due to mining activities, a large area of the puna belt is already authorized to operate by mining activities (SERNAGEOMIN, 2017), so urgent action is needed in order to evaluate the occurrence of the species inside this area.

All four areas (A, B, C and D) are part or connected to three protected areas (Lauca National Park, Las Vicuñas National Reserve and Surire National Monument), all of them belonging to UNESCO International Biosphere Reserve Lauca, designated in 1983, containing a rich variety of fauna and flora and, as shown, with a strong demand by mining operations. However, their their legal status is confusing. Those units belong to the National System of State Protected Areas (SNASPE in Spanish), but much of its area is private, owned by ancestral rights to the Aymara ethnic group (CONAF, 2007). This makes its real protection and conservation difficult, and has also generated a series of conflicts, including the intention in the year 2011 of the government to declare a portion between 5-15% of the Lauca National Park to be used by mining activities, and the disaffection of Salar de Huasco National Park due to demands by local communities, leaving to uncertainties for the conservation of the high Andean ecosystem. Political pressure to re-evaluate Lauca park boundaries are still present by economical forces (Rundel & Palma, 2000), threatening this unique ecosystem in the high Andes. On this regard, Andean cat is a species of concern, not only because being a highly specialized and rare species, with low numbers, restricted distribution and low levels of genetic diversity (Napolitano et al. 2008; Marino et al, 2010; Marino et al, 2011; Reppucci et al, 2011; Cossíos et al, 2012) but also for being a umbrella and flagship species (Simberloff, 1998; Marino et al, 2010), whose conservation entails the protection and encourages public support for the conservation of the high Andean ecosystems.

Distribution modelling using a fine scale resolution allows to define of environmental predictors who influence the occurrence of a species at a finer (i.e.

landscape) scale (Van Gils et al, 2012; Lyet et al, 2013, Nezer et al, 2016) such as topographic or land cover variables, which coarse-scale models cannot detect. Moreover, it allowed us to determine habitat patches, areas of large continuous habitat and small fragments, useful for future population studies at a landscape scale.We strongly recommend this fine scale approaches when the objective is to plan conservation strategies at a landscape level (Lyet et al., 2013). This kind of approaches allows to better understand the relationship of the species with its environment and to direct reliable management and conservation decisions.

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