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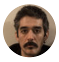

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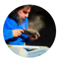

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# Fine scale approach to propose conservation areas for the endangered andean cat (*Leopardus jacobita*) in the chilean dry puna

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ABSTRACT

One of the challenges of working with rare or elusive species is knowing their current distribution. Species distribution modeling (SDM) is a robust approach to estimate the distribution of a species where this information is unknown. The Andean cat (*Leopardus jacobita*) is an extremely rare and endangered carnivore living in the central Andes of South America. This study sought to determine priority areas for the conservation of the species in the dry puna of Chile using fine-scale SDM approaches. The potential distribution of the Andean cat was estimated through Maxent and random forest modeling algorithms. The predictive variables with the greatest contribution to the distribution models included three related to temperature, one to precipitation, one to the distance to wetlands and finally the topographic position index. The total suitable area predicted for the Andean cat was 923.4 km$^2$, which showed a highly fragmented pattern. Based on the information generated by the distribution models, its threats and formal protection, four priority areas were defined. This information will be useful for guiding and prioritizing future actions towards the conservation of the Andean cat in northern Chile.

## 1. Introduction

Rare species are of special concern in conservation because they are often more prone to extinction than common ones (Dobson et al., 1995; Yu and Dobson, 2000). Rarity also makes it challenging to detect such species and estimate their abundance and/or distribution (McDonald, 2004), crucial aspects when developing conservation strategies. Moreover, the lack of knowledge of basic geographic information makes managing conservation programs difficult, even for relatively well-studied species (Anderson and Martínez-Meyer, 2004). In this regard, the estimation of the potential distribution through modeling approaches becomes a useful tool not only to fill existing information gaps in species distribution, but also for conservation purposes (Marcer et al., 2013).

Species distribution models (SDM) seek to characterize the distribution of species through the combination of ecology, geography and statistics, predicting the occurrence of species in unsurveyed areas (Elith and Leathwick, 2009; Franklin, 2009). SDM associate

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environmental predictors with presence/absence observations and develop rules which are used to classify new observations where the values of the predictors are known, but not the response (Franklin, 2009). SDM applications 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 preparation of conservation programs (Guisan and Thuiller, 2005; Franklin, 2009; Liu et al., 2013; Lyet et al., 2013), are useful for rare species or with conservation problems and as a tool to prioritize and develop conservation actions (Anderson and Martínez-Meyer, 2004).

The Andean cat (*Leopardus jacobita*) is among the least known felids in the world, one of only five cat species considered endangered by the IUCN, and the Americas' most threatened felid (Nowell and Jackson, 1996; Villalba et al., 2016). It is an extremely rare species, occurring at low densities (Reppucci et al., 2011; Huaranca et al., 2013). It prefers areas with the presence of Andean bogs known as 'bofedales' and steep-rocky formations, habitats which are naturally fragmented in the landscape (Marino et al., 2010; Villalba et al., 2016). In addition to its ecological importance, the Andean cat is considered sacred by Andean cultures, being part of their traditions and religious beliefs related to fertility and prosperity in agricultural and livestock production (Giraldo, 2015). This symbolic relevance gives this felid added value for its conservation as a mainstay within the rituals and traditions of Andean cultures.

Habitat loss and degradation are of increasing concern in most areas where the Andean cat is present, mainly due to the expansion of agriculture, inadequate animal husbandry practices and water extraction for the mining industry (Villalba et al., 2016). However, there are no studies addressing their effects on Andean cat populations (Zanin et al., 2014). Furthermore, for the northern area of the species distribution in the Andean plateau, suitable habitat is expected to decrease due to climate change (Bennett et al., 2019). Assessing the impact of human activities on ecosystems is a keystone in conservation planning, helping to prioritize areas where urgent action is needed (Brooks et al., 2006). Lack of spatial information of this impact hampers the development of strategies at landscape level. SDMs help evaluate the consequences of habitat loss for local fauna and plan conservation programs for their long-term conservation, especially for felids, which are particularly sensitive to disturbances (Zanin et al., 2014). Since most threats occur on a local scale, a fine-scale approach is needed to apply conservation or management programs correctly.

To date, only a few and very localized studies have addressed the spatial relationship of the Andean cat to its habitat on a fine scale (Marino et al., 2011). This kind of approach can provide relevant information for regional and local biodiversity conservation planning (Lyet et al., 2013). In 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 number of occurrence records for the species, yet it is highly threatened by mining activities (Villalba et al., 2016). The main objectives of this project are: i) to recognize the environmental factors affecting the Andean cat distribution in the dry puna of Chile and predict its environmental suitability, ii) to evaluate and spatially present the main threats for the species in the area, and iii) to propose priority areas for the conservation of the species.

## 2. Study area

The study was conducted in the dry puna of northern Chile (Cabrera, 1968) at altitudes ranging from 3500 to 5200 m.a.s.l., and corresponds to the northern distribution of the Andean cat in Chile (Fig. 1). The dry puna is characterized by a mean annual precipitation between 100 and 400 mm (Cabrera, 1968) and the presence of rivers, lakes and salt flats. It presents a cold climate, showing an annual average temperature of 2 °C, with ranges over 20 °C between day and night, and rainfall of tropical influence concentrated in the austral summer (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. A plant community of wetland grasses called a 'bofedal' is the typical floristic and vegetation complex in watercourses, where cushions of *Oxychloe andina* are the most relevant species (Rundel and Palma, 2000). These areas, as well as the rocky outcrops, are the main source of shelter and food for the Andean cat and are found naturally fragmented and scattered on the landscape of the Andean puna.

## 3. Methods

### 3.1. Species distribution modeling

#### 3.1.1. Occurrence data and identification of samples

Primary occurrence data was obtained through the Andean Cat Alliance (*Alianza Gato Andino* or AGA in Spanish) database with records spanning 1988 to 2014. Inside the study area the database comprised 66 records, 6 of which were skin samples, 32 DNA extracted from fecal samples, 25 records from camera traps and 3 direct sightings (Napolitano et al., 2008; Marino et al., 2011). To ensure there was no spatial autocorrelation between records and to avoid over-representation of local attributes, we selected only one locality per each 5 × 5 km cell (Marino et al., 2011), maintaining its spatial independence. Therefore, the resulting dataset comprised a total of 27 records (3 skins, 4 fecal DNA samples, 17 records from camera traps and 3 direct sightings).

In order to avoid spatial bias in primary occurrence data and to ensure a homogeneous sample, we randomly selected 100 sites in under-represented regions and areas never before sampled (Phillips et al., 2009). Sites were separated by at least 5 km between them and between any occurrence point or previously surveyed site, allowing also to increase representativeness throughout the study area. Within each site we considered a radius of 1 km where we deployed a camera trap with a passive infrared sensor (Bushnell TrophyCam IR). The site where the camera was installed was selected to maximize its probability of capture (McDonald, 2004), preferring locations with indirect signs of presence of the species (i.e., tracks, latrines and/or presence of its main prey, *Lagidium* spp.; Napolitano et al., 2008), but properly representing the habitat heterogeneity of the study area. Cameras were deployed in four different campaigns, between February and December 2015, completing a total of 96 sites. Each camera worked for at least 60 traps/night and was programmed to operate continuously, taking 3 pictures per event and at an interval of 10 s between events. In the same 1 km radius we extensively searched for latrines in the nearest rocky outcrop. One and occasionally two fecal 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, Department of Ecology, at the P. Universidad Católica de Chile for species identification. Identifications were made using fragments of ATP-8, 16 S and two portions of the NADH-5 mitochondrial genes, obtained through polymerase chain reaction (PCR) using primers and conditions published in Johnson et al. (1998). These mitochondrial fragments are broadly used in felid studies because they are well described, polymorphic, and because there is a good collection of reference sequences for the species (Johnson et al., 1998; Napolitano et al., 2008; Cossíos et al., 2012). We repeated 15% of the PCR amplifications of fecal samples for each gene fragment to ensure repeatability of species identification. DNA was extracted from epithelial rectal cells impregnated on feces using a specific kit (QIAamp DNA Stool Mini Kit, QIAGEN, Valencia, California) and following the manufacturer's suggested protocol (Napolitano et al., 2008, Cossíos et al., 2012).

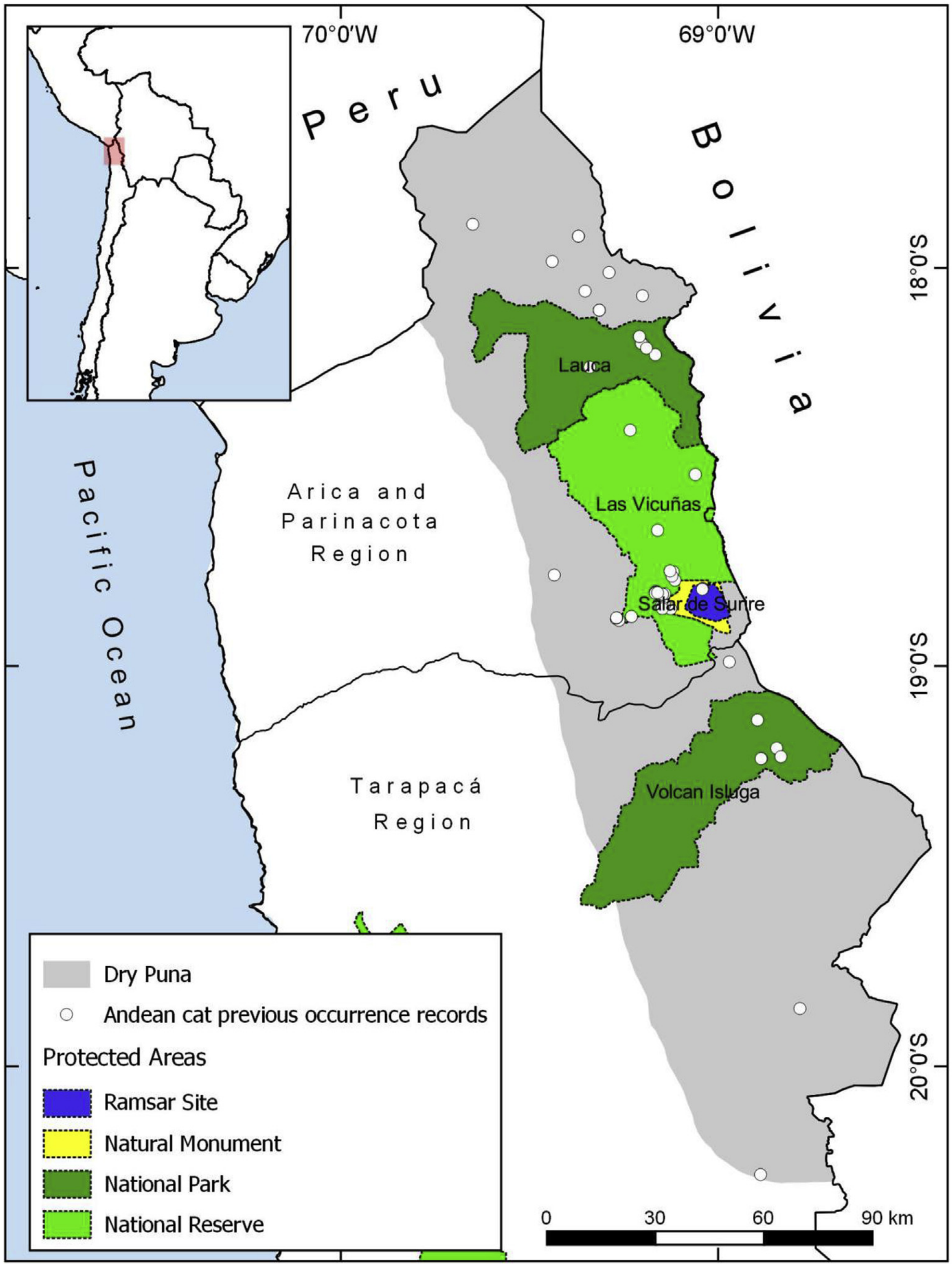


**Fig. 1.** Study area showing the limits of the dry puna and protected areas in northern Chile.

**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 (Topographic position index) | 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) |

**Table 2**
Threat dataset used to calculate Human Influence Index.

| Feature | Spatial resolution | Source |
|---|---|---|
| Human settlements | | |
| Global Urban Footprint (GUF) | 12 m | Esch et al. (2012), 2013 |
| Human access | | |
| Chile Road Network | Vectorial | Military Geographic Institute |
| Human land use change | | |
| Land Cover Chile 2014 | 30 m | Zhao et al. (2016) |
| Mining operations | | Mining Concessions Land registry - SERNAGEOMIN |

#### 3.1.2. Predictor variables

We selected potential predictors based on the biology of the species including both broad scale climatic and finer scale topographic variables (Table 1). 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 the 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 and Elith, 2013). Model parameters were the same as shown in section 3.1.3. Ten iterations were conducted per modeling method. Then, we explored variable contribution for each modeling method, excluding the variables with the lowest scores (i.e., less than 2%). Among the redundant variables (i.e., with a Pearson coefficient > 0.9), those with higher contribution were preferred. Whenever it was suggested that an ecologically relevant variable be excluded through this procedure, we preferred to keep it in the final model (Dormann et al., 2013). This procedure was repeated until all remaining variables were statistically or ecologically relevant.

#### 3.1.3. Modeling approach

Among the different modeling approaches used to build species distribution models, Maxent and Random Forest have proven to be two of the best performing methods (Elith and Graham, 2009; Liu et al., 2013). We used R package dismo (Hijmans and 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 a 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 (Lobo and Tognelli, 2011), but excluding sites with known records (Liu et al., 2013). To avoid them coinciding with occurrence locations, a radius of 1 km from each occurrence location was excluded. This number of pseudoabsences avoids overprediction (Lobo and Tognelli, 2011), which is useful when working with reserve design and for conservation purposes and with rare or endangered species, aiming for a correct classification of absences but increasing the misclassification of presences (Lobo and Tognelli, 2011). To obtain a robust estimate, we ran 100 iterations per modeling algorithm and combined them into one unique model by weighting the area under the curve (AUC) of the receiver operating characteristic (ROC) plot (Hijmans and Elith, 2013).

#### 3.1.4. Model threshold and validation

Since AUC is one of the most commonly used coefficients to measure model performance (Hernández et al., 2006; Freeman and Moisen, 2008), some authors have criticized its use (Lobo et al., 2008; Jiménez-Valverde, 2012). Converting the map to a binary surface using a threshold is useful for performing future analyses as well as for evaluating model prediction reliability (Jiménez-Valverde and Lobo, 2007; Jiménez-Valverde, 2014). Since there are many threshold 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 to design a reserve, maximizing specificity or minimizing commission errors (predicting suitable habitat where it is not suitable) is preferred, so the model will make predictions only in areas where the species is highly likely to be present, avoiding areas with a low probability of occurrence (Barbet-Massin et al., 2012; Liu et al., 2016). For this study, as we were not working with real absences and considering that only a percentage of the pseudoabsences correspond to real absences, we decided to apply a value for specificity of 0.6; this means that we accepted misclassification up to 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 of correctly predicting an absence, overall accuracy (OA), which is the probability that a site (either presence or absence) will be correctly predicted, and Cohen's kappa, which corrects the OA by the accuracy expected to occur by chance (Franklin, 2009; Jiménez-Valverde, 2014).

### 3.2. Human Influence Index

To define the influence of anthropogenic impact 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 and available layers, we selected datasets which represent three categories of human influence (HI) that 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 were assigned to each dataset with respect to 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 collected with Delphi assessment (Supplementary Material S1). Human Influence scores for each dataset were summed and normalized to scale their range from 0 to 100, creating the HII throughout the study area.

### 3.3. Proposal of conservation areas for the andean cat

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

## 4. Results

### 4.1. Species distribution model

#### 4.1.1. Occurrence data and selection of predictor variables

In total, cameras worked for 6255 traps/night and recorded Andean cat presence at 18 different sites (19.1%). A total of 110 fecal samples were collected. Of these, we were able to properly extract and amplify DNA from 99, ten of which (9.9%) were Andean cat. If Andean cat presence was recorded at the same site by both methodologies, only one record was included. 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 to temperature and two related to precipitation were selected, as well as elevation, distance to wetlands, Topographic Position Index

**Table 3**
Selected dataset used in the final modeling approach. Values shown correspond to the mean value for the 100 iterations and the standard deviation is in (). Highest variable contribution for each modeling approach is 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) |

(TPI), land cover and slope (Table 3). Of the selected variables, the ones that showed the highest contribution by either of the two modeling approaches were mean temperature of driest and coldest quarter, mean diurnal temperature range, distance to wetlands and TPI.

#### *4.1.2. Model selection, threshold and validation*

Both modeling approaches showed a 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 the two modeling approaches were similar but with a slight difference: Maxent showed a less conservative approach and predicted higher suitability in the puna belt in the northwestern part of our study area. From the 100 iterations, models were averaged by their AUC and then combined in a single final model. The threshold calculated for a fixed specificity of 0.6 yielded a value of 0.48, which was used to convert the continuous suitability map into a binary one. The 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$^2$, concentrated mostly in the Arica and Parinacota Region, and including areas above 3200 m.a.s.l. In the high Andes and the puna belt (Supplementary Material S2). The suitable areas showed a highly fragmented pattern with more connected areas associated with larger ravines and Andean bogs, whereas non-suitable areas were related mostly to plain areas.

### *4.2. 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 were related to the presence of mining operations and human settlements, followed by areas with roads. Areas with very low or no degree of human transformation (HII ≤ 10) covered 73.5% of the study area, accounting for its low degree of anthropogenic impact. Nevertheless, the spatial configuration of those areas showed a large amount of landscape fragmentation separated by areas with a medium or high degree of human transformation (Supplementary Material S2).

### *4.3. Proposal of conservation areas for the andean cat*

Based on Andean cat habitat suitability, the HII and current protected areas, four geographic areas were selected as priorities to direct programs or actions towards Andean cat conservation (Fig. 2, details on Supplementary Material S2c and S3).

## 5. Discussion

This study represents the first attempt to define conservation areas in northern Chile at a fine spatial scale for the Andean cat, an extremely rare and threatened species. Such approaches are uncommon but useful for identifying critical habitat and designing fine-scale conservation strategies and programs (Lyet et al., 2013). It also provided useful information about environmental requirements for the Andean cat's distribution in the dry puna.

Bioclimatic variables accounting for the main climatic characteristics in the dry puna were selected by Maxent model (Table 3): precipitation concentrated in the austral summer season accompanied by higher temperatures and a strong difference of temperature between day and night (Garreaud et al., 2003). On the other hand, Random Forest gave greater importance to predictors associated with topographic variables (Table 3), which are key variables for the 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 (Villalba et al., 2016), and water availability, associated with the presence of Andean bogs, known as 'bofedales' (Marino et al., 2010).

**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 ([a]) | | | | |
| Agriculture | 6 ([a]) | | | | |

[a] No buffer considered.

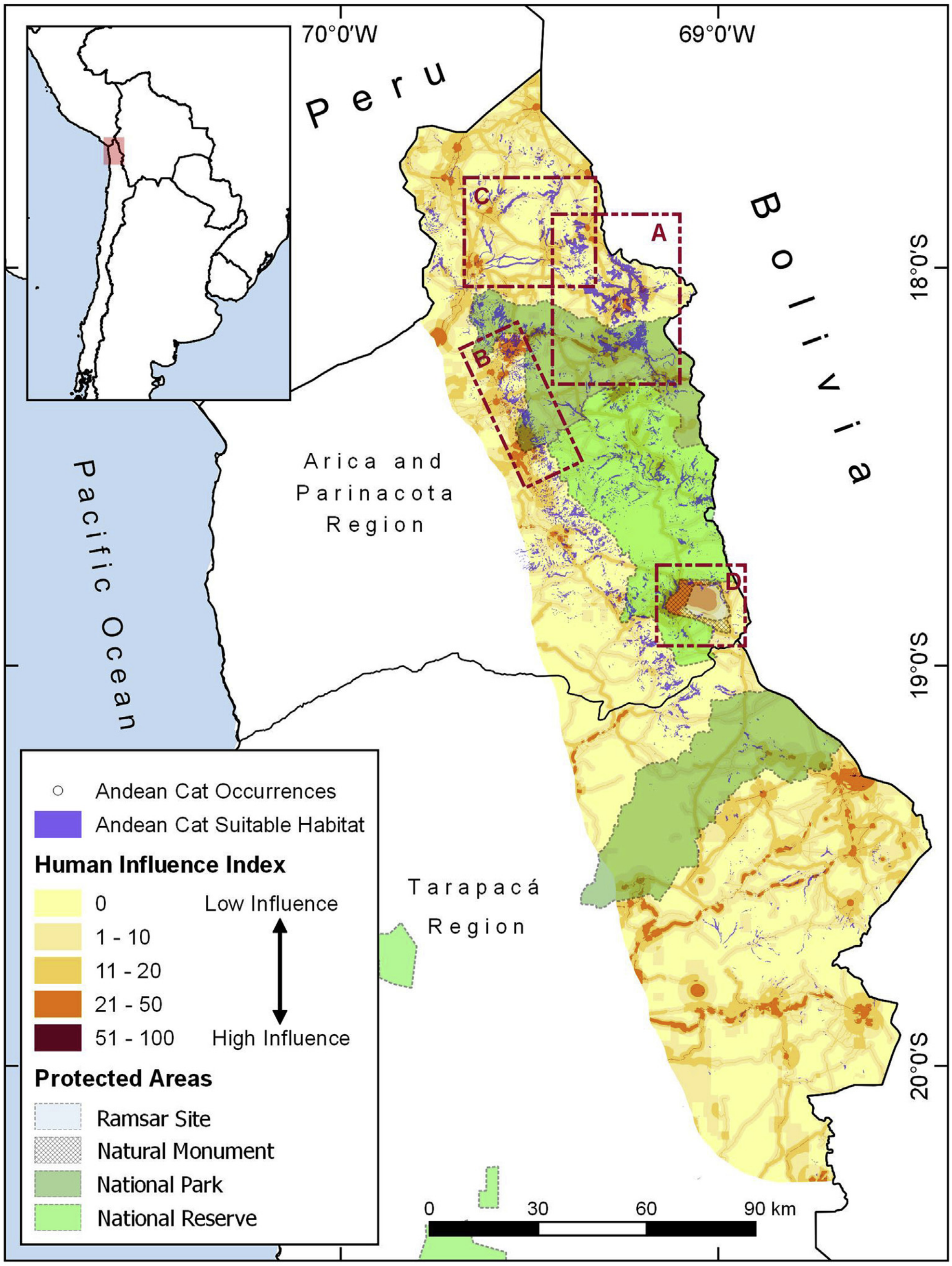


**Fig. 2.** Priority areas (red dotted squares) for Andean cat conservation in the Chilean dry puna. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Although elevation has proven to be a key factor in Andean cat distribution (Marino et al., 2011), in our final models it was not 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 between the two modeling techniques in the variable contribution could be due to their different algorithms in selecting variables and accounting for them in the model construction, but needs further exploration (Franklin, 2009). However, final predictions of both modeling methods were similar and showed a 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), the habitat of its main prey.

All model performance values calculated were high for both modeling approaches. The area under the curve (AUC) of the ensemble Random Forest and Maxent model had a high value (0.93). Since the AUC is not recommended by several authors (Lobo et al., 2008; Jiménez-Valverde, 2012), four alternative accuracy indexes were calculated from a 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, the sensitivity value (0.63) was low. This was expected because we chose a stringent threshold to ensure 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 to areas where it is reasonably certain the species will be found (Wilson et al., 2005). Combining alternative indexes to assess model performance is useful because it overcomes the deficiencies of the different accuracy measurement approaches, being more informative than a single measurement alone. Moreover, the results must be interpreted in the context of the study objectives and the application of the model.

The final binary map showed a fragmented distribution of suitable habitat for the Andean cat, which accounts for its habitat specialization. Rocky outcrops are the preferred habitat for the species which, consistent with our results, are naturally fragmented (Marino et al., 2010, 2011; Villalba et al., 2016). In addition, Andean bogs are frequently surrounded by rocky formations, sometimes covering vast areas along ravines, which could be used as natural corridors. Extensive areas of plains are not preferential for the species but could be used for dispersion between patches. Further studies focusing on the utilization of this matrix of unsuitable habitat by the Andean cat are required to identify if they are being used to cross between patches of suitable habitat.

The main threats for the Andean cat include the presence of human settlements and mining operations, which are well distributed throughout the study area (Supplementary Material S2). This activity is a direct threat not only due to habitat destruction and modification, but also due to water extraction, a scarce resource throughout the Andean cat distribution. Mining is a growing industry in Chile, which is evidenced in the extent of exploration and exploitation concessions granted (SERNAGEOMIN, 2017), so it is expected that this threat may increase in the near future. The demand of the mining sector has drained water sources in the Altiplano, including Andean bogs and salt flats, a key resource not only for the Andean cat and biodiversity in general but also for local communities.

The combined methodology of SDM and HII maps proved useful in locating areas for the conservation of the Andean cat in northern Chile. Four zones were selected as priority to implement management programs for the conservation of this species. Among those areas, we considered Area A as the most important (Supplementary Material S2) because it has a large number of well-connected suitable habitats (238 $km^2$ approx.) and three core areas with a high threat level. Most of this area remains unprotected, with only one section in the south included in Lauca National Park. We strongly recommend that this area in the northeast of the park be included and prioritized as part of formal conservation plans. This zone corresponds to the Parinacota - Cotacotani lagoons, which are not only of interest for Andean cat populations but also for other Andean species (Rundel and Palma, 2000; Márquez-García et al., 2009). Moreover, the Cotacotani lagoons serve as the source of the Lauca, the main river in the basin, making them a key water source for the maintenance of the ecosystem. This area is connected in 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 it is difficult to restructure park boundaries, future conservation and management plans for the park should definitively consider this zone out of bounds.

Future research is needed in Area B to validate model predictions through field surveys. This area has a large surface of habitat suitability, but it has no Andean cat occurrence records. This area is also under threat from mining activities. In fact, a large area of the puna belt is already authorized for mining activities (SERNAGEOMIN, 2017), so urgent action is needed to evaluate the occurrence of the species inside this area.

All four areas (A, B, C and D) are part of or are connected to three protected areas (Lauca National Park, Las Vicuñas National Reserve and Surire National Monument), all belonging to the UNESCO Lauca International Biosphere Reserve. Designated in 1983, it contains a rich variety of fauna and flora and, as shown, with a strong demand by mining operations. However, the legal status of these is confusing. These units belong to the National System of State Protected Areas (SNASPE in Spanish), but much of their area is private, owned by the Aymara people through ancestral rights (CONAF, 2007). This makes real protection and conservation of the park difficult, and it has also caused a series of conflicts, including the intention of the Chilean government in 2011 to declare between 5 and 15% of Lauca National Park for use in mining activities, increasing the uncertainty about the conservation of the high Andean ecosystem. Political pressure to re-evaluate Lauca park boundaries for economic interests is still present (Rundel and Palma, 2000), threatening this unique ecosystem in the high Andes. In this regard, the Andean cat is a species of concern, not only because it is 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, 2011; Reppucci et al., 2011; Cossíos et al., 2012), but also because it is an umbrella and flagship species (Marino et al., 2010), whose conservation involves the protection of the high Andean ecosystems and encourages public support for their conservation.

## CRediT authorship contribution statement

**Nicolás Lagos:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Project administration, Funding acquisition. **Jaime Hernández:** Conceptualization, Formal analysis, Methodology, Software, Resources, Writing - review & editing, Supervision. **Dayana Vásquez:** Methodology, Formal analysis, Investigation, Writing - review & editing, Data curation, Formal analysis. **Cristian Sepúlveda:** Investigation. **Francisco j. González-Pinilla:** Investigation, Writing - review & editing, Formal analysis. **Magdalena Bennett:** Methodology, Writing - review & editing. **Rodrigo Villalobos:** Investigation. **Agustín Iriarte:** Investigation, Resources. **Claudio Correa:** Investigation. **R. Eduardo Palma:** Investigation, Resources, Writing - review & editing, Formal analysis.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jaridenv.2020.104200.

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