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Short Communication

Tourism and human computers offer new tools to monitor Patagonia's top carnivore

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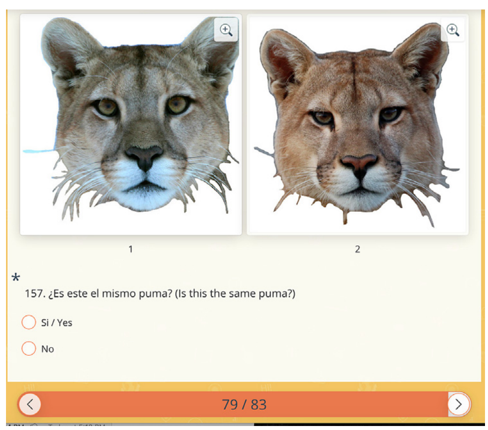
HIGHLIGHTS

- Monitoring data essential for conservation are lacking for many species.
- Without training, people are powerful interpreters of information and patterns.
- Guides in Chile and people in the USA differentiated between individual pumas.
- We provide puma abundance estimates for the Torres del Paine UNESCO Biosphere.
- People in tourism can monitor wildlife to increase global conservation capacity.

GRAPHICAL ABSTRACT



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ABSTRACT

Monitoring wildlife populations to determine changing abundance is the basis for conservation strategies and interventions. Monitoring, however, is expensive, and we lack baseline data for countless species and landscapes around the globe. One solution is to utilize methods that leverage observations collected by everyday people. Humans are not only excellent sensors for diverse data, but possess a remarkable ability to process data and differentiate patterns with minimal training. Here, we explored the potential for people, including guides who work in tourism in southern Patagonia, to determine whether paired photographs of puma (*Puma concolor puma*) faces were the same individual, akin to a computer-led Siamese network analysis. Overall, participants performed well (average score of 92.2 %) and we detected no differences in local people versus those from the USA, or differences due to differential experience working with pumas. Based on these results, we built a historic capture-recapture dataset of individual pumas collected by local guides and report annual abundance for a portion of the Torres del Paine UNESCO Biosphere in southern Chile, an area lacking such data and of critical conservation for the species. Our results highlight the innate capabilities of human computers and their potential for contributing to wildlife surveys in novel ways to increase science capacity.

1. Introduction

Monitoring wildlife populations to determine changing abundance is the basis for all conservation strategies and interventions. Consequently,

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there is a rich and constant literature on new and improving techniques and technologies to support more efficient and more accurate estimates of wildlife abundance. The reality, however, is that monitoring is expensive and time-consuming, and therefore we lack baseline data for too many species across countless landscapes around the globe. One solution to this dilemma has been to design methods that capture and leverage observations collected by everyday people (e.g. i-Naturalist data, Hochmair et al., 2020; Christmas bird counts, Meehan et al., 2019; tourist observations, Rafiq et al., 2019).

Humans are not only excellent sensors for diverse data collection (Goodchild, 2007), but possess a remarkable ability to process data and differentiate patterns with minimal training (Koch et al., 2015). Consider, for example the difficult task of differentiating between the faces of individual humans using computer-based analytical tools. Although automated facial recognition based on convolutional neural networks from classified training data are fast developing, they still require large datasets and super computers to provide reliable results (e.g. brown bears, *Ursus arctos*, in Clapham et al., 2020; harbor seals, *Phoca vitulina*, in Birenbaum et al., 2022). On the other hand, humans can differentiate between categories of objects, including people's faces, after just one experience with them (Fei-Fei et al., 2006; Lake et al., 2011). This realization has spawned new approaches to image classification based on "one-shot learning," and paired image comparisons called Siamese neural network analyses (Koch et al., 2015). Nevertheless, the use of humans as classifiers may still prove the best and cheapest strategy for some classification projects, as well as an exciting intersection between technology and participatory science (Van Horn et al., 2014). In the case of conservation monitoring, involving local institutions and local people also increases people's motivation to conserve resources as well as the likeliness of achieving conservation objectives (Waylen et al., 2010; Palmer et al., 2020).

Across Patagonia, we lack current estimates of puma abundance or monitoring data to evaluate their status, and yet, ongoing conflict with livestock makes living with pumas a relevant conservation conundrum (Rinehart et al., 2014; Ohrens et al., 2021). Pumas also lack the spots or stripes that facilitate easier individual identification, hindering the use of traditional camera-trap methods to identify individuals (Alexander and Gese, 2018). Therefore, we explored the potential for people to determine whether paired images of pumas (*Puma concolor puma*) from Chilean Patagonia, were the same individual, mimicking one-shot learning experiments and Siamese neural network analyses (Lake et al., 2011; Koch et al., 2015). Specifically, we tested the ability of puma guides working in the Torres del Paine UNESCO Biosphere to differentiate individual pumas from photographs of their faces, and compared their performance with that of a group of US-based people who also work with pumas in North America. We hypothesized that if indeed people were able to differentiate individual pumas based on visual cues, that there would be no difference in the performance of Chilean puma guides and US-based participants, nor an impact of years of experience working with pumas on the ability to differentiate between individuals. Based on people's performance, we then generated puma abundance estimates for a portion of the UNESCO Biosphere based on local guide observations.

2. Materials and methods

2.1. Study area

The puma guides who participated in this study work in the Torres del Paine UNESCO Biosphere Reserve in southernmost Chile, where they contribute to rapidly-growing puma tourism activities. Puma tourism has occurred in the area to some degree for approximately 20 years, but surged in growth beginning in 2014 (Tortato et al., 2020; Cárdenas et al., 2021). The pumas in this region are the most observed of any population in their range, and provide unique opportunities for photography and data collection (e.g. Cárdenas et al., 2021). Additional information about the region can be found in Ohrens et al. (2021).

2.2. Testing participant ability to differentiate between individual pumas

We created an online test in Spanish and English through Surveylegend (www.surveylegend.com), during which we asked participants to respond as to whether two photographs of puma faces were of the same animal (binary response, yes/no); this approach mimics "one shot learning" experiments in which participants match objects in paired images (e.g. Lake et al., 2011) and computer-based Siamese neural network analyses that include tandem comparative analyses of paired images to create neural networks capable of classifying novel material (Koch et al., 2015) (Supplementary material 1). The test began with an explanation of the study and our objectives. The study was performed in accordance with ethical guidelines from the Belmont Report (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979), and we assumed informed consent by all participants that voluntarily completed the survey.

All photographs were of wild pumas from Chilean Patagonia. We utilized 1–3 high quality photographs of 26 known independent pumas captured with hand-held digital cameras for a final dataset of 55 images with which to create the test; kittens were not included. These pumas were marked during research efforts ($n = 11$) (Elbroch and Wittmer, 2012) or monitored intensively during filmmaking and tourism in situ. We were also cognizant of selecting images of individual pumas made within a 1-year timeframe of each other, so as to avoid differences that may occur over longer time frames (e.g. new scars) that might influence performance. Then we cut out the faces of the pumas in Adobe photoshop so as to remove any background information, including research collars, ridgelines, habitat or associated kittens that might influence participants' answers. We created 80 unique pairings from these photographs using random selection with replacement (Fig. 1), as our goal was to keep the test short enough so as to avoid mental fatigue that might influence performance. Participants were asked to complete the survey on a computer, and not a phone, so that images were larger; the program also allowed them to expand images and zoom in to look closely at different features, like scars or freckles on the nose. Participants were also able to skip a pairing and to navigate forward and backward as they desired. There was no time limit to the test.

2.3. Evaluating performance

We recruited puma guides that work in and adjacent Torres del Paine National Park in person and via word of mouth, and people who had not visited Chile but had some experience working with pumas in North America via an email blast to colleagues. As part of the survey, participants were asked to describe their experience working with pumas in years.

Using significance testing and single variable regression models, we tested whether 1) local puma guides and US non-guides performed equally on the test, and 2) experience explained any variation in performance. Because of variable performance in responding correctly to different questions, we also conducted a post-hoc test to determine whether sunlight influenced performance. Sunlight creates shadows that can distort features, and therefore could explain variation in performance. Specifically, we tested performance on questions in which both photographs were taken in even light (i.e. overcast days or in shade), versus photo pairs in which one was taken in direct sun and the other in even light.

2.4. Puma abundance estimates

To illustrate the utility of this type of data, we built a historic capture-recapture dataset of individual pumas, including dependent offspring, collected by local guides working fulltime in the field during the summer seasons from October 2017 through March 2020. The sampling area was approximately 100 km^2 of the Biosphere on and adjacent the "Peninsula," which straddles Torres del Paine National Park and Estancia Laguna Amarga (Fig. 2a).

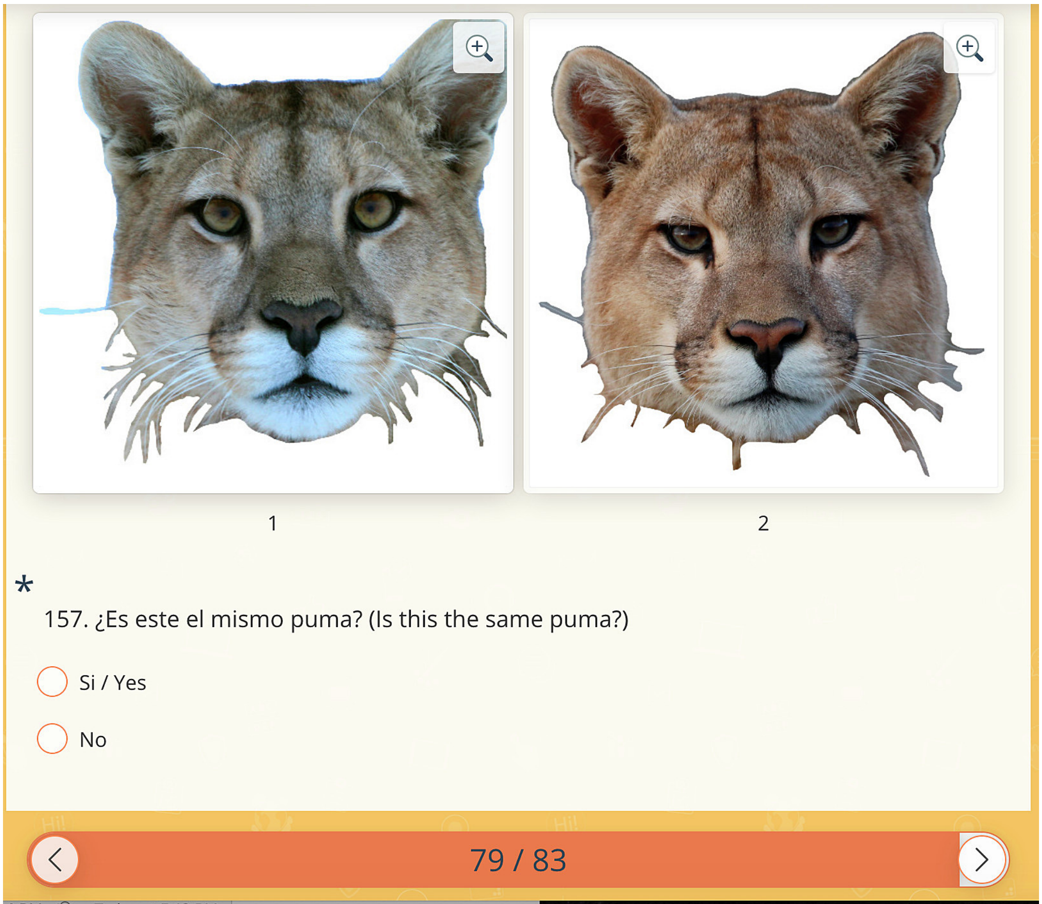

Fig. 1. A screenshot from the online survey in which participants were asked whether two photographs were of the same puma. In this case, the correct answer in no.

We estimated puma abundance and 95 % confidence intervals for the summer monitoring data from 2017 to 2020 with Chapman's (1951) modification of the Lincoln-Peterson estimator, which assumes a closed population and that all animals have an equal probability of being captured/recaptured. For each 6-month summer season (October–March), we divided the monitoring data into two 3-month intervals. Pumas seen in the first three months of summer were defined as capture events, and individuals subsequently viewed during the second three months of summer as well were defined as recapture events.

3. Results

3.1. Participants and survey results

Twenty-one Chilean guides participated in the survey, of which 16 completed the full survey, and 18 people from the USA participated, of which 16 completed the full survey. We included those who did not complete surveys in analyses of individual questions, but excluded them from analyses comparing overall performance on the test.

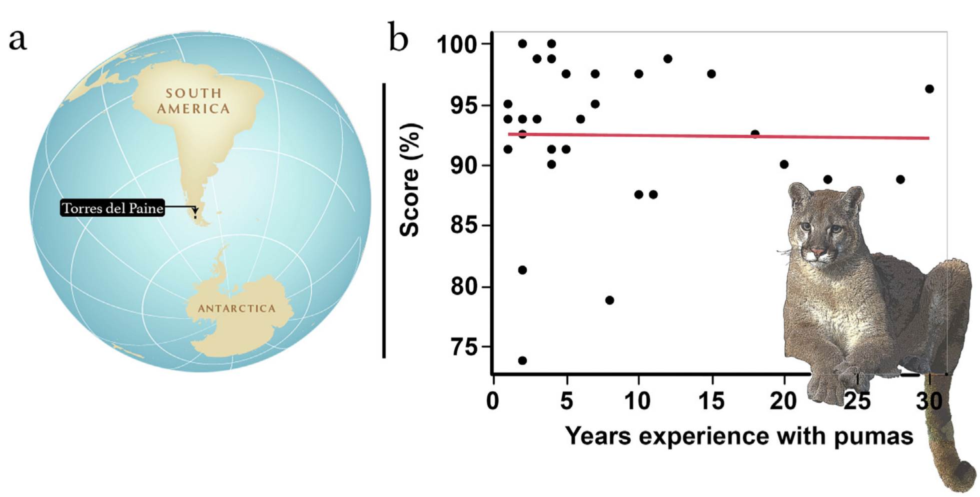

Fig. 2. a) Location of the study area. b) Participant scores with respect to participant experience with pumas in years. The red line is the regression line showing no significance of experience on score.

Overall, participants exhibited a high success rate in differentiating between individual pumas. On average, 91.4 % ± 1.3 *SE* of people answered each question correctly (n = 32–39). Chilean puma guides and people from the USA performed equally well ($F_{1,29} = 0.0008$, $p = 0.978$), and experience working with pumas did not impact performance ($F_{15,13} = 0.715$, $p = 0.735$) (Fig. 2b).

We found a significant difference in performance on questions in which both images were taken in even light made by shade or overcast days, versus those in which a pair of images included at least one image in which the puma was in direct sun ($F_{1,78} = 4.669$, $p = 0.034$). Mean performance for questions with images of pumas in even light ($\bar{x}$ = 92.78 % ± 1.47 *SE*) were higher than those in which at least one image was a puma in direct sun ($\bar{x}$ = 82.67 % ± 2.94 *SE*).

3.2. Abundance

We cataloged detections (0,1) for 41 individual pumas (17 males, 24 females), inclusive of dependent kittens, across the three seasons. Abundance exhibited overlapping confidence intervals across years, and Table 1 elucidates captures, recaptures and annual abundance estimates (Table 1).

4. Discussion

Guides and non-guides proved equally adept at differentiating between individual pumas, creating new opportunities for participatory science to contribute to the monitoring of the most emblematic puma population in the world, and perhaps support for similar methods on other wildlife around the globe (note similar methods have long been used for whales; Smith et al., 1999). Though not a direct comparison of methods, participants in our study outperformed automated facial recognition of individual unmarked species based on convolutional neural networks (83.9 % for brown bears in Clapham et al., 2020, and 88 % for known harbor seals in Birenbaum et al., 2022), highlighting the innate capabilities of human computers and their potential for contributing to wildlife monitoring in novel and meaningful ways (Rafiq et al., 2019). Participant performance could be improved as well, by only including photographs captured in even light, such as on overcast days.

Here, we utilized guide-generated data to estimate historic puma abundance for a UNESCO Biosphere Reserve lacking this information, and an area of particular conservation concern. Puma sightings did not include spatial data or the range over which these pumas wandered beyond the area sampled, and therefore should not be extrapolated to estimate density (Rinehart et al., 2014). Nevertheless, it is clear that the area hosts a high puma density, and likely one much larger than reported for other areas across their range in North and South America (1.62–2.02 independent pumas/100 km^2 in Murphy et al., 2022).

If photographic data inclusive of location data and time stamps were combined with survey data (route and distance traveled), one could design a robust spatially-explicit capture-recapture (SECR) analysis (Royle et al., 2009) to not only determine puma abundance but also population dynamics over time. SECR is considered best practice by many for estimating the abundance of low-density, cryptic carnivores (e.g. Broekhuis and Gopalaswamy, 2016); monitoring large carnivore abundance is critical given that they are disproportionately important to ecosystem health and resilience, and particularly sensitive to anthropogenic impacts. Photographic documentation could also be used to generate capture-recapture data on individuals tracked over time, ideal for survival analyses (e.g. leopards Balme et al., 2017), as well as data on reproductive ecology (i.e. timing and evidence of courtship, litter sizes;), conspecific interactions (Charpentier et al., 2008; Elbroch et al., 2017), and other complex ecological questions vital to creating species conservation strategies.

As the scale of monitoring increases, however, more humans will be required for analyses or it may be more efficient to invest in designing an automated facial recognition program to differentiate individuals. Human computers then become essential in creating the classified data needed to train facial recognition software. The raw photographs processed by humans and computers alike can be collected by qualified guides working in the field, or by anyone on an open source platform (e.g. a phone app) where photos could be uploaded with ancillary data. Growing wildlife tourism in combination with human-centric methodology provides new opportunities for participatory science to bridge the gaps in rare species monitoring needed to support global conservation.

Table 1
Number of individual pumas detected in each 3-month session, number of recaptures, the estimate of puma abundance (number of individuals) and standard deviations for each season.

	2017–18	2018–19	2019–20
First 3 months	20	19	14
Second 3 months	24	25	16
Number of recaptures	14	12	7
Abundance	37.5	43.3	36.4
SD	5.8	8.8	10.4

CRediT authorship contribution statement

LME: Conceptualization; Data curation; Formal analysis; Methodology; Project administration; Roles/Writing - original draft. RM: Data curation; Investigation; Resources; Writing - review & editing. DG: Data curation; Investigation; Resources; Writing - review & editing. NL Data curation; Investigation; Resources; Writing - review & editing. JC: Data curation; Investigation; Resources; Writing - review & editing. OO: Investigation; Project administration; Writing - review & editing.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.162916.

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