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PEOPLE, CITIES, AND BIRDS IN LATIN AMERICA

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Dedico esta tesis a dos personas que perdimos repentinamente el 2018:

A mi tío Lucho Rondón, quién amó a su tierra con un orgullo incomparable
y a la tierra de otros con una curiosidad insaciable,
y a Claudia Pezo, quién solo quisó aprender de la naturaleza pero la sociedad la falló.

“Move slow and empower people” - Ruha Benjamin

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Grad school is isolating, therapy and antidepressants are lifesavers, but to be simplistic, we know from evolutionary biology that phenotype is equal to environment plus genotype, if we don't do something to change the environment, it doesn't matter what we do as far as self-care. Grad school is not only isolating but it often makes you feel powerless. UChicago was the place where I most personally learned that it doesn't matter if you do the right thing the way that laws ask you to– if an institution like UChicago, the second biggest employer in the city, and the biggest on the South Side, decides they don't want to recognize you as a union, they can go against what the NLRB tells them, and instead, decide they want to change the law. I've met so many amazing and inspiring people through our union, the Graduate Students United, through our labor council, UChicago Labor Council, and through the UChicago Student Activist Network; people who taught me about organizing, about the importance of seeing the connections between all struggles, and about building power. Because the most important thing I think I can say about our union is: we've been around since 2007, we might not be recognized, but we've accomplished incredible things. Just in our division, we hadn't seen a raise since the GAI was established. When we dropped union cards, we got a raise. When we went on strike, we finally got a commitment to a yearly raise to match inflation. We don't need to be recognized to act, function, and succeed like a union– our power lies in our labor and in our acting collectively. I hope that you will also seek out your colleagues and neighbors wherever you are to envision what a better world could be.

A better world for me has only been imaginable because of the connections I have made with other people. I am so thankful to have friends and family throughout the world who have been supportive and encouraging. In Chicago, in addition to the folks that I've met through the university, I've had the luck to meet and hang out with urban farmers to not forget our connection to the land, I've had the luck to fall into an incredible book club with amazing women and their amazing families– I want to make a special shout out here to the Knoblauchs for feeding me, teaching me about tidyverse, discussing dumb things like Ben Affleck's pajamas as though it were the most serious thing, and going on dog walks with me when I was on the verge of panic attacks. Thank you for being incredible neighbors. Speaking of neighbors, thank you to everyone who at one point was part of Mother Pilsen. I've learned so much from your refusal to give in to a life of work, letting work be work, and home be home. Jacobo Zambrano, thank you so much for helping me find new ways of seeing the world. I can't wait to continue making art with you. The Oak Park DND crew brought storytelling into my life and I'm so happy that our six hour escapist sessions with ridiculous amounts of middle school food could be a needed respite from graduate school. My friends from high school also continued to be a source of joy– wherever we ended up meeting, whether I was at a conference, visiting my parents, or zoom birthday hangouts. There is of course my lifelong emotional support from my family - both blood and chosen, including but not limited to the Ugarte-Villalobos, my long list of tías, my grandmother Marjorie Lott, and my WCS family. Running workshops with y'all is both intense and invigorating.

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CHAPTER 1

INTRODUCTION

When I proposed my dissertation research, my goal was to understand how nature uses urban space and how urban space affects nature. My research questions inquired about patterns in urban community assemblages at continental and local scales, effect of human behavior on community assemblages, genetic and morphological differentiation of birds along an urban gradient, and morphological differentiation in bird species with introduced and native populations. In the process, I wanted to *really* get to know two very different Peruvian cities that have been a home (Lima and Iquitos) and two smaller cities near them (Huacho and Nauta). I thought that doing multiple scale research would be easy: global citizen science datasets, like eBird, are open access; high-throughput sequencing makes lab work more accessible; satellites could capture high resolution images and Google published them online; travel is now relatively cheap; connections I had nurtured would help me get the necessary permits. Four years since that proposal (and six years since entering graduate school), I not only understand the true scope of that ambition, but have come around to questioning the assumptions and implications that fed it.

Research in urban ecology and evolution is fundamentally different from many other types of ecological research, because of the omnipresent and complicated spatial-political logistics. While many biological stations exist for ecology and evolution research (e.g. Cocha Cashu in Manu National Park, Perú; La Selva in Costa Rica; Smithsonian in Barrio Colorado Island, Panamá; Itasca in Clearwater, United States; the Ponds in Ithaca, United States, among others), urban area study designs have to consider both public and private ownership (with jurisdictions often overlapping), lots smaller than our study species' home ranges, fragmented/novel habitats, dense human populations, the attitudes of these humans, and a plethora of additional variables, some of which we have history and information for, and some for which we do not. And so, researchers aim to design investigations that take these into account or control for them as possible, using remote sensing strategies, citizen science, and institutional collaborations (often with schools). In designing my own research, these strategies started to become the focus of my questions—I wanted to know: where do we get these remote sensing techniques? Who designs them, who has access to them, and who implements them? Who are the citizens that participate in citizen science? Why do they do it? How do they find out about it? Which institutions are collaborated with? How are connections made? The *how* we do science became paramount to defining the science I wanted to do. And so, my questions changed. The chapters that make up this final dissertation merge my initial proposed questions with a lens informed by the questions that developed while pursuing them.

The chapter that follows, "The case for field-based geospatial analysis in urban planning and conservation," compares turn-key image classification methods (methods included in ArcGIS and accepted as a default) with visual methods (looking at an image and estimating how much of it is a certain land use type) and finds that, at least for my field sites in Nauta, visual classification of satellite images was more accurate than the ArcGIS algorithms. In the chapter, I make a case for why this is an important result and why it might be the case in other places. To a large extent, the chapter itself came from my own fight with technology access. Without access to ArcGIS on my laptop, working from home or from the field was extremely difficult. Open source software was buggy, and my laptop could not handle the sort of processing needed for high-resolution images. The laptop available to me through our program that could handle the processing did not have ArcGIS, and I worked from student trial accounts for about three months, getting locked out periodically, before finding out there was a GIS laboratory in the library. I was frustrated with the situation I was encountering while studying at one of the wealthiest universities in the world, and I could only imagine what it would take to create maps that governments would take seriously in any other situation. To explore this problem, I wrote this chapter and found that for some questions, you do not need costly software or sophisticated, innovative methods. Maps can be made by hand, and they can be analyzed by eye (I am, of course, not the first to say this—there is a long tradition in participatory mapping, with some recent examples found in [117, 103, 27, 28]). Underlining this fact allows us to take away technical capacity as a barrier to urban and conservation planning. Instead, local researchers and urban residents need only have interest and access to the systems that define their cities.

The next chapter, “People still think there’s no nature in cities, but want to know more”, focuses on that first part of what citizens need to participate in defining their cities and the nature within them: interest. Urban populations have long been described as “apathetic” to nature, and “scared” of wildlife [151]. Before 2013, I may have said the same. Growing up between different cities in Perú and the U.S., my most defining “natural” experiences were outside of the city: watching macaws and other parrots feed at clay licks (*Ara* spp., *Amazona* spp., *Brotogeris* spp., *Pionus* spp., among others); sea lions (*Otaria flavescens*) on the coast surrounded by penguins and their babies (*Spheniscus humboldti*), thousands of cormorants (*Leucocarbo bougainvillii*, if lucky, *Phalacrocorax gaimardi*), and Inca terns (*Larosterna inca*) holding anchovies as they courted each other; and millions of wintering Tree swallows (*Tachycineta bicolor*) roosting in the Floridian countryside. However, living in Lima after college, a city of around 10 million people, alongside other conservation practitioners reminded me that some of the experiences that brought me every-day magic were filled with urban wildlife (I think of: biking to work in fog, swallows (*Notiochelidon cyanoleuca*) swooping near me and the Scrub blackbirds (*Dives warczewiczi*) noisily filling up the trees; when I lived in NYC, long walks at any time of the day by the Hudson river, turtles in the Bronx river). To explore how people cared for their homes, Rocío Lopez de la Lama, Armando Valdés Velásquez, and I launched *Limanatural*, a community blog for people to talk about what they were doing for their environment in Lima. While the blog is now on hiatus, the years that we worked on it showed me that urban residents are not “apathetic” to or “scared” of their surroundings. This chapter was born out of wanting to know how people felt and thought about nature in their homes. While there are differences among urban residents of different cities in how much they “know” about their surroundings (insofar as the questions I asked reflected that), it was clear that the majority of the (973!) people that I talked to wanted to know more about birds in their cities—their names, where they hang out, how to find them. Interest in birds—connection to nature—by urban citizens exists.

The chapter after, “Biodiverse places have more to lose to cities”, showcases the wide-reaching scientific questions we can ask when citizens are interested in their natural history—and are taking data in a consolidated network. It also brought me back to one of my original proposal questions: Are urban bird assemblages in Latin America different from their respective regional species pools? Using eBird data for 37 cities from northern Mexico to southern Chile, I compare what avian community assemblages look like within cities to the regional species pools. This dataset is enormous: 18,393 checklists contained 2,113 species of birds, for which I have clutch size, hand-wing index, tarsus length, beak measurements, tail length, and IUCN status. These were not amassed just from eBird data, but also through open databases, collaborations ([148], through Joseph Tobias), and in-museum measurement. It was hard to decide on just one specific ecological question, but we settled on asking whether biodiverse communities may be losing more species due to urbanization. We found, as the title suggests, that they may indeed be doing so. We explore this further by looking at something called “assemblage vulnerability,” a measure of how likely the assemblage is to go extinct ([186]). When we compare this measure between urban and rural assemblages there is not much difference. However, if we look at IUCN status, urban assemblages hold less threatened assemblages, suggesting that by this measure, urbanization may be affecting some of the most threatened birds. This dataset still holds a dense amount of information that was only possible to put together by the generosity of citizen scientists in an articulated virtual network (eBird), and scientists, mostly early-career but not always, adamant in sharing their data openly (e.g. [164]).

Finally, my conclusion restates my main findings and explores further research, identifying which I will take on myself and which might be better pursued in other contexts. While

I did not answer all of my initial questions, I do believe that I explored how nature uses urban space and how urban space affects nature. The difference is that in these definitions of nature, nature includes humans. I learned that we do not always have to go for the most sophisticated methods to answer questions or get data—the most important thing is having on-the-ground knowledge, and natural history. This is the same in urban areas. I learned that people are interested in knowing more about birds, and that they are, for the most part, excited to talk to you about it. I learned that whether a bird is vulnerable to extinction might have more to do with how large its community is and that the most vulnerable and threatened birds may not be supported in cities. I learned that all of these dimensions are important to understanding the process of ecology and evolution research, and in the context of environmental and conservation decision-making. Did I get to know Lima, Iquitos, Nauta, and Huacho better? Yes—but like all relationships with place and time (and thus, the realities of evolution itself), those are life-long endeavors.

CHAPTER 2

TOWARDS A FIELD-BASED GEOSPATIAL ANALYSIS

2.1 Abstract

A persistent problem in urban wildlife research is the acquisition of land use data classified into appropriate categories at a relevant resolution. Using Nauta, a small city in Peru proposed as a model of sustainable development, we assess different methods' abilities to characterize urban landscapes. While administrative boundaries can be found either through Open Street Maps or government databases and broad land use categories can be georeferenced from zoning reports, the data necessary to answer questions about spatial effects on wildlife in cities at finer scales is not readily available throughout much of the world, thus requiring image processing and classification to conduct analyses. A further challenge in obtaining these data is the limitations of available algorithms to accurately classify images when there is variety within categories (e.g., buildings that differ in shape, color, and size), and similarity between them (e.g., grass and trees are both green). Here, we present comparisons of four methods of image classification, using hand-coded images as the reference images: visual estimate of satellite imagery, visual estimate of hand-coded images, a pixel-based maximum likelihood algorithm with training data, and an object-based maximum likelihood algorithm with the same training data. We also compare species abundance linear models for the Black Vulture (*Coragyps atratus*) to show the potential impact of misclassification. Given important considerations of time, ease of use, number of images, and institutional support, visual estimate of satellite imagery was the best methodology. This result simplifies technical expectations, thereby facilitating local research, self-directed growth, and governance.

2.2 Introduction

Understanding how wildlife occupies urban space is important for anyone who lives in a city– especially if one wants to advocate for a particular group or ecological process within the urban landscape as an urban planner, wildlife conservation practitioner, or community organizer. For example: design elements of roads can de-incentivize deer and reduce vehicle accidents [63, 136, 82]; high biodiversity can influence well-being and ecosystem services [71, 102]; urban greenspace can provide ecological corridors or sanctuaries for endangered species [129, 6, 54, 116]; neighborhood community coherence [71], and even sustenance [124, 85]; and knowing the population biology of urban pests, like pigeons, mosquitos, or rats, can help assess zoonosis risk [161, 3].

In order to study these urban wildlife interactions, researchers need geospatial information at an appropriate scale and resolution [8]. The composition of space at a high spatial resolution is important, particularly when talking about wildlife with small home ranges, such as the Brown rat (*Rattus norvegicus*, where home ranges can be as small as 30 m; [30]) or the House Wren (*Troglodytes aedon*, with an average home range of 0.4 hectares; [98]). Additionally, some species' core and home ranges can vary widely, such as the scavenger Black Vulture's (*Coragyps atratus*) core range, which can seasonally vary from 3 m^2 to 2,800 m^2 [83]. To characterize land use in urban spaces today, researchers can use open access geographic layers from places like Open Street Maps, or request processed images and land use layers from local governments or consulting firms. However, for many places around the world, the already processed layers from open sources like Open Street Maps or the government are not available, either due to lack of crowd-sourced interest or lack of capacity within the government. At the same time, hiring consulting firms or start-ups are often prohibitively costly.

An alternative approach is for researchers to process satellite images in order to create their own geographic layers, usually with algorithms that use machine learning techniques and training data in order to classify either pixels or objects within the image into features of interest [33, 79]. Most of these algorithms were designed for images acquired through Landsat at coarser resolutions than those needed when thinking about local effects in urban neighborhoods (f. ex., [175, 195]). For example, different satellites have different resolution grid cells and have different capacities for capturing spatial extent. To obtain the sort of land use data that would characterize the urban space in ways relevant to wildlife, satellites like Sentinel-2 and CNES/Airbus provide images with spatial resolutions of $\leq$ 10 m grid cells [188, 39, 184]. Through services like Google Maps and Google Earth Pro, many of these images are now largely available, ushering a new frontier of high spatial resolution data [79].

The algorithms used to classify pixels work by taking a pixel and characterizing the distribution of their spectral signature [34]. They use that signature by comparing the spectral signature to the training data provided and assigning a probability that it belongs to a particular “class” or “feature” (type of land use) [34]. This training data is held within a signature file created by the researcher and provides many examples (regions of interests, ROIs) of each “class” or “feature” to create a range within which pixels can fall into [34]. Object-based algorithms work by detecting the boundaries around objects and using the object’s spectral average to classify all the pixels within the object [200]. But there are technical issues with these algorithms at a high spatial resolution. At a coarser resolution, the differences between urban and other land uses are clear. At a finer resolution, there is intra- and inter-spectral variety for classes [200]. For example, buildings can differ in shape, color, and size, complicating what the “average” spectral and object parameters are for the full class, and some classes can look extremely similar despite being two different types of land use (see images in Fig. 2.3).

Computer scientists are working on improving algorithms for use with high-resolution images [79]. However, accessing new computational methods for remote sensing is a notoriously long process. The Defense Advanced Research Projects Agency, an agency within the Department of Defense has been using global positioning system (GPS) data and information systems (GIS) since the 1950s, when they first proposed GPS as an tool for science in order to avoid international accountability in surveillance efforts, yet the technology necessary to use these for science was not widely available until the 1980s [197, 47, 187]. Currently, the best methods are through very costly software (like eCognition) or through additions to already costly software (such as Feature Analyst on ArcGIS) [200, 179]. An alternative method that is not costly in of itself is Orfeo Toolbox, an open source plug-in for open-source QGIS. Here, other issues can arise, such as conflict between developers' timelines—As of Jun. 2018, Orfeo Toolbox was no longer compatible with QGIS, and its independent user interface did not run on affordable commercially available computers. While the development of better algorithms on QGIS is possible, this requires expertise in programmatic languages. Thus, the algorithms used for these coarser resolution images are still the most technologically sophisticated available for researchers working outside of a GIS center, so long as they have access to the Spatial Analyst addition to ArcGIS.

In this study, we use high-resolution satellite imagery to characterize the urban landscape of Nauta, Loreto, Peru. Nauta is a city located at the confluence of the Marañon and Ucayali rivers in the Amazonian rainforest within the department of Loreto [11, 32]. It was founded in 1830 by Manuel Pacaya Irarica, a Native leader of the ethnic group Kokama, and, as of 2017, has a population of 29,963 people [32]. It serves as an important river port, and is the terminal end for the only paved road (∼99 km) that extends out of Iquitos, the capital of the department [11]. Loreto is the largest department in Peru (∼36.9M ha; between the Equator and 9° south), and one of the most biologically and culturally diverse regions of the country [11]. Nauta has also been proposed as a model for Amazonian development [65], particularly because there are many plans for infrastructure, including paved roads and railroads, connecting the city to the rest of Peru through terrestrial transportation [11]. In this context, the city of Nauta, alongside the other major cities and towns in Loreto (Iquitos, Yurimaguas, and Requena), is an important setting for understanding urban development and ecology as deforestation related to infrastructure ramps up next to protected land covering 18% of Loreto under various management schemes [11]. In this study, we use high-resolution satellite imagery with three goals: (1) characterize Nauta's urban landscape; (2) assess the performance of four different methods of image classification; and (3) assess whether method of image classification affects the ability to model species abundance.

2.3 Methods

2.3.1 *Image collection*

One satellite image comprising all of urban Nauta was downloaded from Google Earth Pro. Ten sample points were chosen within the city, spread out to cover as much of urban Nauta as possible, recorded on a global positioning system (GPS; brand Garmin) on the ground, and then uploaded to Google Earth Pro. Each point was at least 200 m away from the other (Fig. 2.1). Images were downloaded for each point, where each point was at least 500 m from each edge of its image as jpg files, georeferenced, and saved as raster datasets (TIF files). Satellite image date was May 25th, 2016, resolution size was 0.43 m x 0.43 m pixel size, and copyrighted to CNES/Airbus in 2019 [1]. Image was used with permission.

2.3.2 *Describing Nauta's urban landscape & hand-coding*

The large satellite image was used to delineate the overall urban area in ArcMap (part of ArcGIS suite). The image was georeferenced and projected (UTM18S-WGS1984). It was delineated by creating a polygon that connects the outermost points of the road network in the city (that is, where a road leads to the last structure for 1 km). Surface area was calculated by using the Calculate Geometry tool in ArcMap (see green outline in Fig. 2.1).

To characterize Nauta's urban landscape, the sample raster datasets were uploaded and buffers were created around the sample points (one at 100 m, "local", where most blocks are ∼100 m, and one at 500 m, "neighborhood", representing a buffer a little further out from one block radius) on ArcMap. These buffer distances were chosen somewhat arbitrarily to represent the variability within and between avian species' core and home ranges. Each

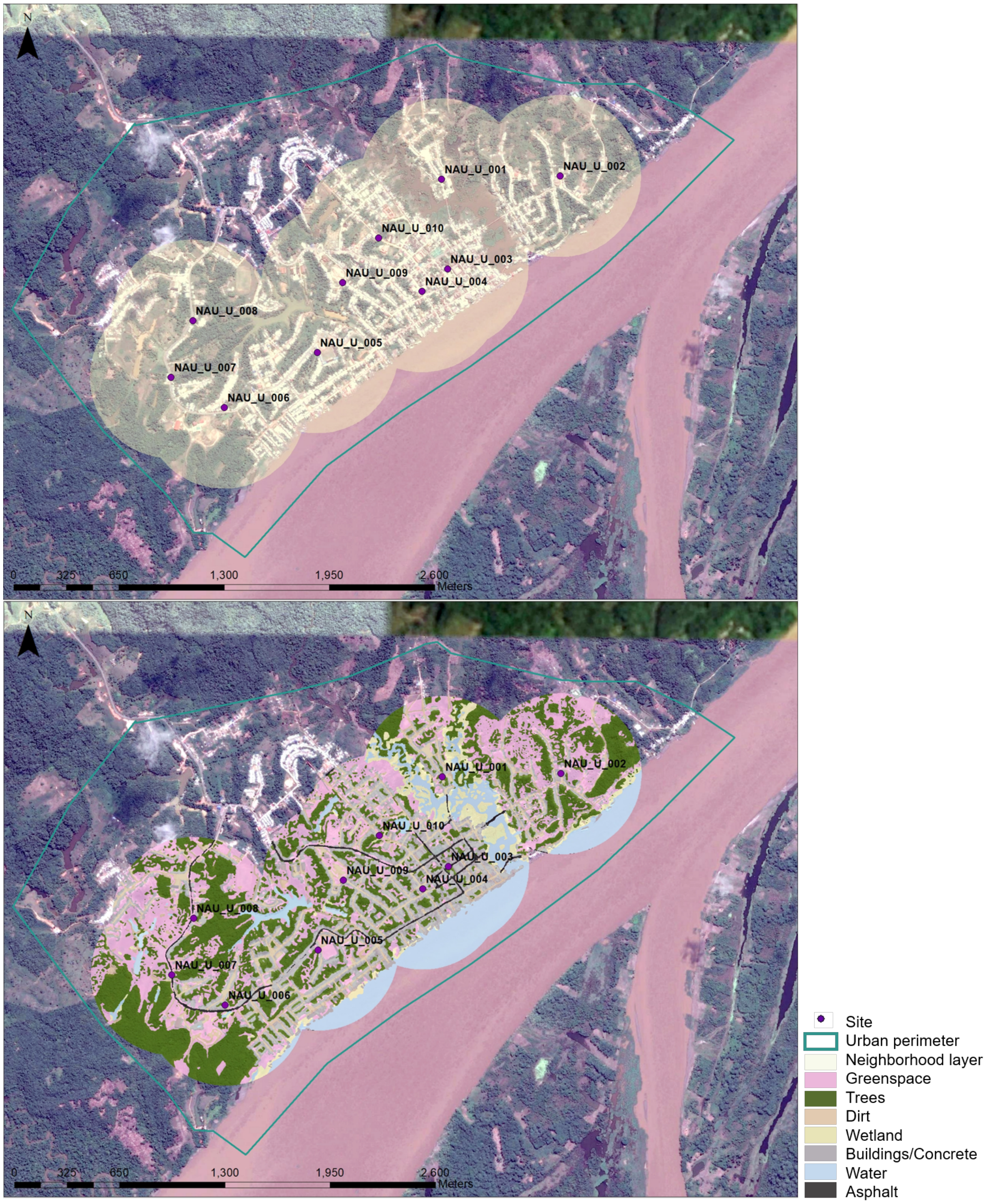

Figure 2.1: (Top) Satellite image of Nauta, Loreto, Peru, with perimeter polygon and sample sites (overlaid on merged 500 m buffer site images, "neighborhood layer"), and (bottom) hand-coded image of "neighborhood layer." Downloaded from Google Earth Pro; Image ©2019 CNES/Airbus, Image ©Maxar Technologies, Image Landsat/Copernicus. Imagery date: May 25th, 2016. Used with permission.

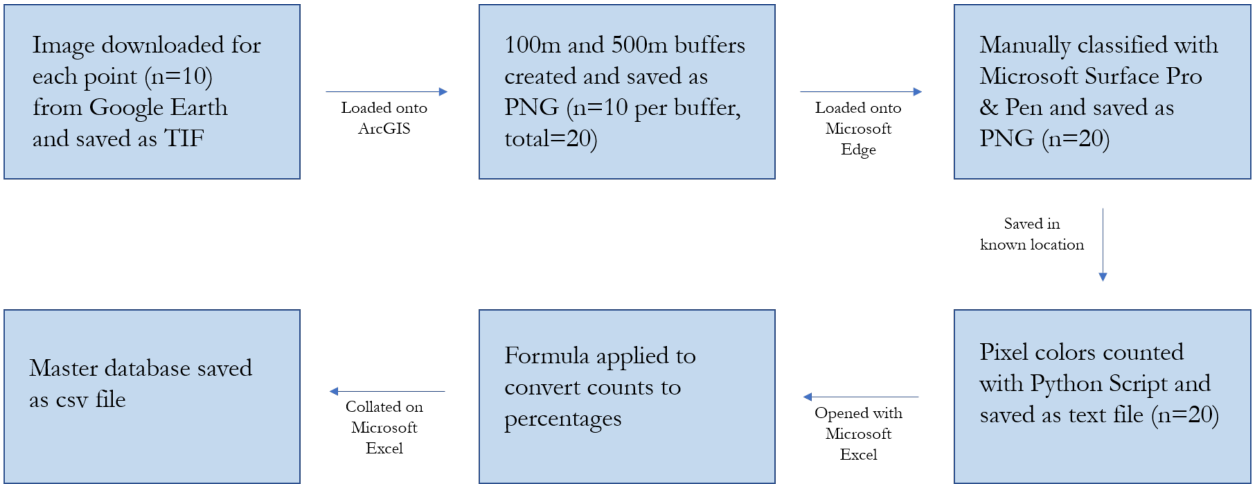

Figure 2.2: Process flow to manually classify images and describe Nauta's urban landscape.

buffer image was then downloaded onto a PDF editor, and, using a Microsoft Surface Pro and a Microsoft Surface Pen, hand-coded into feature classes of interest (greenspace, dirt, asphalt, trees, wetland, water, and buildings) by Piland and saved as a PNG. A Python script was written to identify how many pixels of each color are in each image. Percent coverage was calculated for each image and each class (140 combinations) using the usual formula:

$$\text{percent coverage} := \frac{\#\text{pixels}_{\text{class}}}{\#\text{pixels}_{\text{total}}} \cdot 100\%.$$

Percentages were then entered into a master database (see Fig. 2.2 for this process). The 500 m buffer images were also georeferenced and merged to create a hand-coded neighborhood layer. This method is considered the reference method because it incorporates firsthand and local knowledge of the landscape in classing (thus, a measure of ground-truthing), and computer counting methods for the numerical calculation.

2.3.3 Image classification methods

We compared four different methods of image classification: visual estimate of satellite imagery, visual estimate of hand-coded imagery, a pixel-based maximum likelihood algorithm, and an object-based maximum likelihood algorithm. Both algorithms were run on ArcMap using the same training data. The training data included 20 ROIs per feature class of interest to represent the class completely without manually classifying the whole image [33, 34]. An additional class was included, “shadow”, to control for the potential that shadow would fall into trees or asphalt, the two darkest classes in the images [200].

Visual estimate of satellite imagery with local knowledge. A worksheet was created that included the satellite images buffered at 100 m and 500 m and prompts to visually estimate how much of each image (in percent cover) was represented by each feature class. Velasquez completed said worksheet and Piland entered percentages into a master database.

Visual estimate of hand-coded imagery with local knowledge. A worksheet was created that included the hand-coded images buffered at 100 m and 500 m and prompts to visually estimate how much of each image (in percent cover) was represented by each feature class. Piland completed the worksheet before running the Python script (see “Describing Nauta’s urban landscape & hand-coding”) and entered percentages into a master database.

Pixel-based maximum likelihood algorithm. The georeferenced satellite 500 m buffer images were merged to create a complete layer of the neighborhood extent. The unsupervised maximum likelihood image classification algorithm available on ArcMap was used with the training data signature file to class the complete layer. Piland clipped this layer with the buffer polygons to re-create the 100 m and 500 m buffer images (this time classified by pixel). Attribute tables were then created to count the pixels per feature class. Percentages were calculated and entered into a master database, excluding the shadow percentages.

Object-based maximum likelihood algorithm. The full neighborhood layer of satellite images was object-segmented using the Segment Mean Shift tool in the Spatial Analyst toolbox of ArcMap (Spectral detail = 20, gives importance to spectral differences in features, maximum available; Spatial detail = 20, gives importance to how close features are in the image, maximum available; Min. Segment Size = 20 pixels, default; Band indexes = 3, the number of spectral bands in the downloaded image). The maximum likelihood classification algorithm was then run on the object-segmented layer using the same training data signature file. This layer was then clipped into the 100 m and 500 m buffer images and attribute tables were created to count the pixels per feature class. Percentages were calculated and entered into a master database, excluding the shadow percentages.

2.3.4 Comparisons of classification methods

Comparisons of image classification methods were made along four axes: time the method took to complete, differences between percent cover per image, differences by pixel (where available), and impact on construction of a linear species abundance model for the Black Vulture (*Coragys atratus*). Black Vulture (*C. atratus*) is a common avian pest in Nauta. The hand-coded + Python method used to describe Nauta's landscape was considered the reference method, as it has the highest amount of local knowledge and supervision, while using the computer to count pixels.

Each step's time to completion was estimated and divided by number of images, where appropriate. For example, hand-coding an image took about the same amount of time between images. However, some steps, like writing the Python script to count pixels by color, were one-time costs and therefore inappropriate to be divided by number of images. Average accuracy (as defined by the difference between a reference method's percent cover of a class in an image and the tested method's percent cover of the same class in the same image) was divided by time it took to complete the method.

Each 100 m and 500 m image's percent cover/class was included in a master database. To facilitate comparison, differences between the reference method's and other methods (per image per class for a total of 140 data points) were calculated. Differences were compared using summary statistics and distributions within each feature class to see whether particular methods were better than others at detecting specific feature classes at both extents.

The two neighborhood layers classified by the image classification algorithm were compared to the reference neighborhood layer on a pixel-by-pixel basis. The reference layer was recolored using Python such that each feature class had a unique value along the grayscale, making it easier to create an accurate attribute table. Feature classes were valued at an appropriate value to be able to identify what was correctly classified in the raster layer using the Raster Calculator tool on ArcMap between the manually classified neighborhood layer and the algorithm-generated ones. Using the resulting attribute tables, we calculated the percentages of correctly classified pixels in the layer generally and per feature class in both methods. The equation used to identify the cells correctly identified by each algorithm was:

$$\text{cell identity} := \text{value}_{\text{manual}}^{3} \cdot \text{value}_{\text{algorithm}} \cdot 3.$$

This equation was arrived at by trial-and-error, resulting in unique values for every condition given the values assigned to each feature class in these layers. It is not generalizable.

We created three general linear models describing the mean number of individuals of Black Vulture (*Coragyps atratus*) at observation points using the glm function (family=gaussian) in RStudio v.1.2.1163 [153, 158]. Abundance data was obtained by going to each sample point and counting the number of *C. atratus* individuals observed in a ten-minute interval. These data are part of a bird community dataset compiled by Piland and other colleagues for another project. The first model proposed one variable (local asphalt) as the most important in predicting the mean number of *C. atratus* individuals in each observation point, because this species is known to scavenge in human areas. The second model proposed adds another variable (neighborhood wetland) as important, given that many open-air markets are near wetlands. The third model proposed adds another variable (neighborhood water) as important for the same reason as neighborhood wetland. Akaike's Information Criterion was calculated with a correction for small sample sizes (AICc) using the MuMIn package v.1.43.15 [16]. All three models were compared within and between classification methods.

2.4 Results

2.4.1 Time comparison

The fastest method for this study (n = 20 images) was the pixel-based algorithm (690 minutes), followed up by visual estimate of satellite imagery and object-based algorithm (both at 760 minutes) (2.1). The slowest method for this study was visual estimate of hand-coded images (3220 minutes). Visual estimate of hand-coded images had the best accuracy/time spent (closest to 0), while the object-based algorithm had the worst accuracy/time spent.

Table 2.1: Image classification methods with the steps and requirements to complete them (assuming computer has i5 processor and 8 GB RAM) and the time it will take to complete them per image, and n = number of images to classify. Average accuracy/time spent takes the mean difference between the reference method and alternate method (where each difference is the difference between the percentage of a particular class in an image detected by reference method – percentage of a particular class in an image detected by alternate method; closest to 0 refers to most accurate on average for time spent).

			Method, Total Time (min.), (Avg. Accuracy/Time Spent)				
			Hand-coding and Python	**Visual Estimate**	**Hand-coding and Visual Estimate**	**Pixel-based Algorithm**	**Object-based Algorithm**
			72*n+60	38*n	98*n	31.5*n+60	32*n+60
Step	**Requirements**	**min/image**	Reference	1.88e-06	-3.03e-22	1.67e-05	5.91e-06
Satellite/Aerial Images	Access to Internet	2 min	*	*	*	*	*
Georeferencing	GIS software	15 min				*	*
Training Data	GIS software	(60 min*n)				*	*
Worksheet Creation	Editing software	20 min		*	*		
Visual Estimate	Ability to see	6 min		*	*		
Hand-coding	A computer pen *or* printer, scanner and pen	60 min	*		*		
Python Script	Programming knowledge	(60 min*n)	*				
Layer Creation	GIS software	3 min				*	*
Object-Segmentation	GIS software	0.5 min					*
Algorithm Run	GIS software	0.5 min				*	*
Data Entry	Database software	10 min	*	*	*	*	*

2.4.2 Describing Nauta's urban landscape

Nauta's surface area was measured as 749.51 hectares (top image in Fig. 2.1). The neighborhood layer covers 440.44 hectares, 58.76% of the total surface area (bottom image in Fig. 2.1). The feature class that covers the largest percentage of the neighborhood layer is Trees

(30.96%) and the class that covers the smallest percentage is asphalt (1.41%). Between these extremes, land use is as follows: greenspace (24.3%), buildings/concrete (17.81%), water (12.49%), dirt (8.64%), and wetlands (4.39%). Average composition of images varied by the spatial extent classified. At the local scale (100 m), an average site (n=10) is composed of buildings/concrete (28.8%), trees (27.92%), greenspace (24.94%), dirt (10.7%), asphalt (4.59%), water (1.82%), and wetland (1.23%). At a neighborhood scale (500 m), an average site (n=10) is composed of greenspace (29.68%), trees (26.83%), buildings/concrete (18.54%), water (13.15%), dirt (5.72%), wetland (4.8%), and asphalt (1.28%). At a local scale, the two most abundant feature classes were buildings/concrete (most abundant in 4 sites; maximum 64.3% of NAU_U_003, site at the main plaza; its minimum coverage is 9.3% of NAU_U_008; Fig. 2.1 for site distribution) and greenspace (most abundant in 4 sites; maximum 49.4% of NAU_U_004; its minimum is 7.9% of NAU_U_003). In the remaining two sites, trees were the most abundant feature class (maximum 54.4% of NAU_U_002; minimum is 6.6% of NAU_U_003). Water and wetland were the least abundant feature classes/site, each absent in eight sites. At a neighborhood scale, the most abundant feature class was trees (most abundant in 4 sites, maximum of 64.9% of NAU_U_006; minimum of 7.1% of NAU_U_008). Buildings/concrete was the second most abundant feature class (most abundant in 3 sites, maximum of 29.2% of NAU_U_010; minimum of 0.7% in NAU_U_008). The least abundant feature class/site was asphalt (least abundant in six sites, minimum of 0% in NAU_U_002). Water was absent in only one site (NAU_U_008), and wetland was least abundant in the remaining three sites (all under 1%).

2.4.3 Percent cover differences

Geospatial layers and images resulting from these image classification methods, and the respective percent covers for an example site (NAU_U_010) can be found in Figure 2.3 and Table 2.2.

The narrowest distribution around the 0% difference is the visual estimate of hand-coded

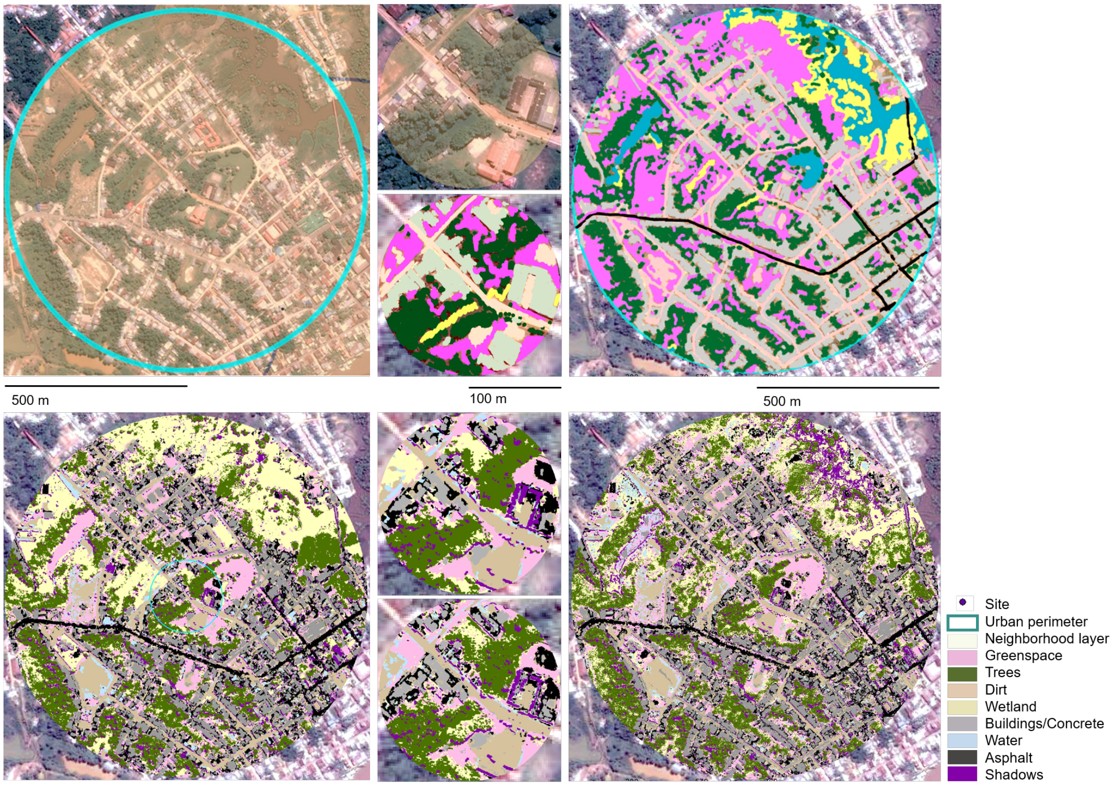

Figure 2.3: Site NAU_U_010. Clockwise, larger images, beginning left top: Satellite image ©2019 CNES/Airbus, hand-coded image, pixel-based classified image, and object-based classified image ("neighborhood" spatial extent). Middle column starting at top moving downwards: Satellite image ©CNES/Airbus, hand-coded image, pixel-based classified image, and object-based classified image ("local" spatial extent). Table 2 shows percent cover for different land uses per method. Imagery date: May 25th, 2016. Used with permission.

Table 2.2: NAU_U_010 land cover percentages based on classification methodology and spatial extent. See Figure 2.3.

Class	Reference 500m	Visual + Sat. 500m	Visual + Hand 500m	PixML 500m	ObjML 500m	Reference 100m	Visual + Sat. 100m	Visual + Hand 100m	PixML 100m	ObjML 100m
Buildings/ Concrete	29.20%	30%	40%	16.35%	15.27%	29%	25%	25%	9.70%	8.47%
Greenspace	26.10%	20%	20%	13.46%	11.86%	24.40%	25%	20%	16.38%	14.72%
Trees	20%	20%	10%	19.17%	19%	30.30%	35%	40%	25.71%	25.63%
Asphalt	1.60%	5%	5%	11.02%	11%	0.20%	0%	0%	9.73%	9.88%
Dirt	9.30%	10%	5%	11.81%	11.71%	13.20%	15%	10%	17.67%	17.06%
Water	7%	5%	10%	3.60%	2.98%	0%	0%	0%	3.58%	3.59%
Wetlands	6.80%	10%	10%	16.33%	21.82%	2.90%	0%	5%	9.75%	12.99%
Shadows	NA	NA	NA	8.26%	6.46%	NA	NA	NA	7.47%	7.67%

images (mean: 00.40%; range: -22.90% - 50.40%; std. dev.: 8.06%; Fig. 2.4a), although visual estimate of the satellite imagery's distribution is not much wider, and its mean is closer to zero (mean: 00.14%; range: -22.90% - 55.40%; std. dev.: 9.28%; Fig. 2.4a). From the algorithm methods, the object-based method has a mean closer to 0% difference (-01.23%; pixel-based mean: -1.92%; Fig. 2.4a), but the spread (range: -68.10% - 77.42%; std. dev.: 15.51%; Fig. 2.4a) is wider than that of the pixel-based method (range: -24.06% - 73.32%; std. dev.: 13.29%; Fig. 2.4a). Greenspace was consistently underestimated across scales and methods (Fig. 2.4b), particularly in site NAU_U_002 (site closest to Marañon river, the largest water feature in the study area), and NAU_U_008 (closest site to the rural perimeter). Buildings and concrete were consistently underestimated by the algorithm methods (Fig. 2.4c). The largest difference in detection between the visual estimate methods and the algorithm methods was for the class wetlands (Fig. 2.4d). Distribution shape (approximating a normal distribution) seems to hold in comparing the local spatial extent distributions and the neighborhood spatial extent distributions (Fig. 2.4a). However, the neighborhood spreads are largely wider than the local spreads (Fig. 2.5a-b).

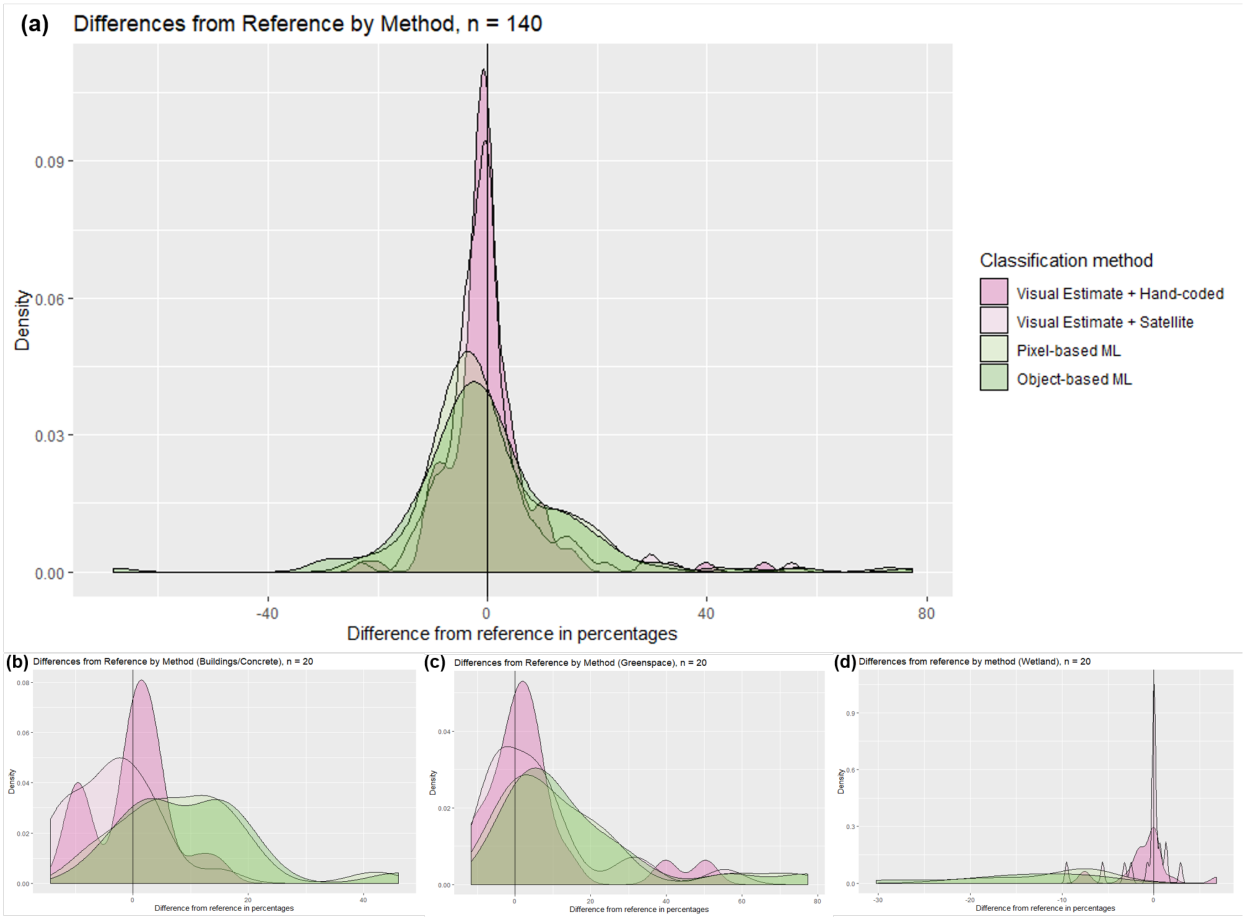

Figure 2.4: Distributions of percent difference between reference method's percent coverage and tested classification method's percent coverage. Distributions represent (a) all classes + scale (n = 140 per method); (b) greenspace (n = 20 per method); (c) buildings/concrete (n = 20 per method); and (d) wetlands (n=20 per method).

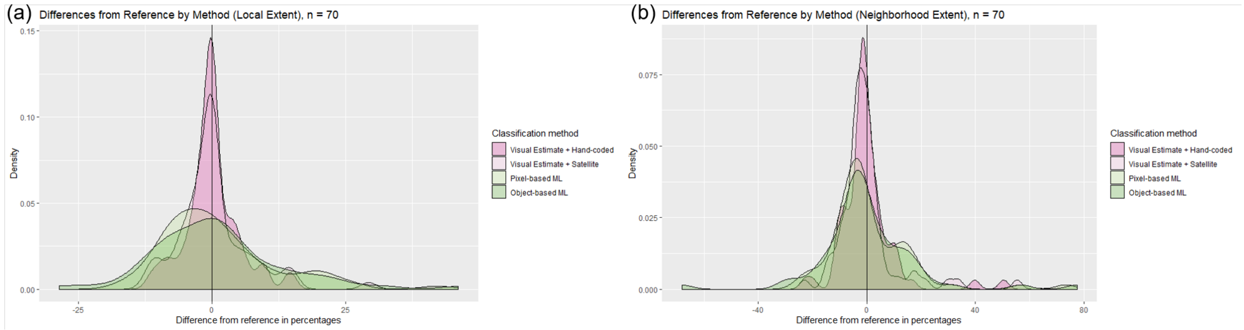

Figure 2.5: Distributions of percent difference between reference method's percent coverage and tested classification method's percent coverage at a: (a) "local" spatial extent (100 m buffer), and (b) "neighborhood" spatial extent (500 m buffer).

2.4.4 Pixel-by-pixel comparison

Both algorithms had an overall accuracy rate of around 40% (pixel-based at 41.97% and object-based at 40.24%; Fig. 2.6). The only two classes that were correctly identified over 50% of the time were water and trees for both image algorithm methods (water was correctly classified 66.03% of instances in pixel-based and 66.17% of instances in object-based; trees were correctly classified 65.59% and 56.3% of instances, respectively). Of the incorrectly classified coverage, most was classified as greenspace (16.7% of pixel-based; 22.04% of object-based). Yet, out of all classes, greenspace was the worst detected (79.8% misidentified by pixel-based; 85.08% by object-based). Shadows represented 6.93% of the layer classified by the pixel-based method, and 5.91% of the layer classified by the object-based method.

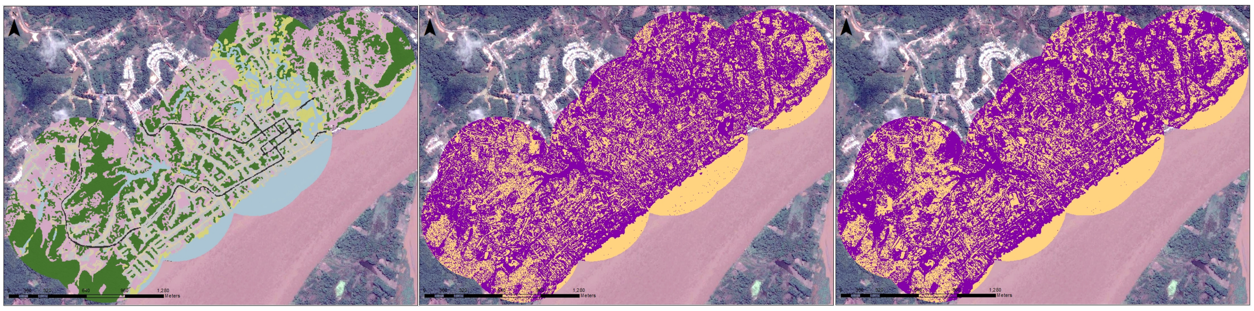

Figure 2.6: Comparison of neighborhood layers: (left) hand-coded image, (center) accuracy layer of classified image (pixel-based), and (right) accuracy layer of classified image (object-based). Accuracy layers represent the pixels that were classified correctly (orange) and incorrectly (purple) in relation to the hand-coded image. Base satellite image downloaded from Google Earth Pro; Image ©2019 CNES/Airbus, Image ©Maxar Technologies, Image Landsat/Copernicus. Imagery date: May 25th, 2016. Used with permission.

2.4.5 Species abundance model

For all methods, the first model (one variable, local asphalt coverage) had the smallest AICc (see Tab. 2.3), indicating the smallest amount of information loss. Only the visual estimate of satellite images had significant p-values associated with both the first model and the third model (three variables). Coefficients became more disparate in orders of magnitude and positive/negative between methods as variables were added.

Table 2.3: Results of generalized linear models (Gaussian) for Black Vulture (*Coragyps atratus*) under each method. All computed values have been rounded to the hundredths place. Models and computations were performed on RStudio V.1.2.1163 [153, 158] using the MuMIN package [16]. Significant p-values are indicated with * (<0.05) and ** (<0.001).

A. GLM - One Variable

(Mean No. Individuals of Black Vultures ∼ Local Asphalt Coverage)

Methods	**Visual + Sat**	**Visual + Hand**	**PixML**	**ObjML**
Coefficients				
Intercept	15.27**	15.15**	10.79	9.97
Local Asphalt	-104.48	-90.41	-14.76	-7.911
Residual Degrees of Freedom	8	8	8	8
Residual Deviance	719.7	724.3	1028	1033
AICc	81.14	81.21	84.71	84.76

B. GLM - Two Variables and Interaction

(Mean No. Individuals of Black Vultures ∼Local Asphalt Coverage + Neighborhood Wetland Coverage + (Local Asphalt Coverage*Neighborhood Wetland Coverage)

Methods	**Visual + Sat**	**Visual + Hand**	**PixML**	**ObjML**
Coefficients				
Intercept	12.19	7.545	70.46	51.57
Local Asphalt	-81.89	-40.71	-452.8	-325.11
Neighborhood Wetland	36.53	107.65	-326.07	-198.38
Interaction	-209.19	-664.39	2540.44	1667.45
Residual Degrees of Freedom	6	6	6	6
Residual Deviance	682.6	619.9	776.6	806.5
AICc	95.61	94.65	96.9	97.28

C. GLM - Three Variables and Interaction

(Mean No. Individuals of Black Vultures ∼ Local Asphalt Coverage + Neighborhood Wetland Coverage + Neighborhood Water Coverage + (Local Asphalt Coverage*Neighborhood Wetland Coverage* Neighborhood Water Coverage)

Methods	**Visual + Sat**	**Visual + Hand**	**PixML**	**ObjML**
Coefficients				
Intercept	67.45**	10.99	323.1	6.954
Local Asphalt	-656.48**	-82.83	-1282.7	494.775
Neighborhood Wetland	-274.55**	471.18	-1608.2	-89.48
Neighborhood Water	-554.26**	-23.44	-9899.3	-664.78
Asphalt * Wetland Interaction	-6741.31*	-3877.86	8567.4	-509.35
Asphalt * Water Interaction	5809.04**	483.1	57590	1612.22
Wetland * Water Interaction	4775.63**	-2508.56	47748	3123.66
All Three Interaction	NA	20193.38	-312525.9	-16050.73
Residual Degrees of Freedom	3	2	2	2
Residual Deviance	32.38	141.8	660	562.6
AICc	200.13	Inf	Inf	Inf

2.5 Discussion

2.5.1 Nauta's urban landscape & small cities

The surface area calculated through our methods (749.51 hectares) cannot be validated with official records since the official delimitations of Nauta as a city are not defined [196]. However, with this size and a population of just over 29,000 [32], by some criteria, Nauta would not be considered a city (c. f. [69] defines the smallest functional urban area as 50,000 inhabitants). Yet, in Peru, Nauta is considered a city because it has more than 5,000 inhabitants [48]. This definition's motivation is to give name and status to places with the intention of permanence [48]. This highlights some of the different perceptions of what urban areas are and the geographic bias within the current definitions of urban [69, 95]. Despite Nauta's small size, the ecological processes within the city likely have an urban signature (in particular, in sites where there is >50% buildings/concrete cover, like NAU_U_003). Overall, Nauta's land cover is almost 1/3 trees, then greenspace, then buildings. As you zoom into the city, the average pattern switches to trees, buildings and then greenspace (neighborhood) and then buildings, trees, and greenspace (local). If urban areas are defined by the percentage cover of impervious surfaces [12], then the spatial extent relevant to research questions can render the study site urban. Furthermore, greenspace is land cleared by humans as the urbanizing process continues, and, in that sense, even at the most zoomed out viewpoint, Nauta is majority cleared land. Therefore, understanding the ways in which ecological processes in small cities differ based on the spatial scale at which it is analyzed can give us some insights on how ecological processes could be affected during a city's growth and development.

2.5.2 Comparisons of classification methods

The method which one may choose to classify satellite imagery is influenced by a variety of factors, including manpower, expertise, equipment and software access, and question.

As far as the four different axes by which we compared the methods, the visual estimate of satellite imagery was just as fast as the object-based image classification algorithm and more accurate. From the species abundance models we constructed, it is clear that the differences in accuracy can lead to different results. Given that the defining land uses of an urban area in respect to wildlife are that of buildings/concrete and greenspace (Fig. 2.4), the fact that they are both underestimated and incorrectly classified by algorithms strengthens the case for visual estimates. As far as the differences between classifying at a local spatial extent and neighborhood spatial extent, the shape of the distributions in differences seems similar, while the differences themselves are higher at a neighborhood spatial extent (Fig. 2.5).

While the algorithms we used were not consistently accurate (Fig. 2.6), there is an active area of computer science research focused on making current algorithms better or constructing new ones for high-resolution satellite imagery [79]. In almost all cases, algorithms work better with a higher amount of training data (a time-consuming task that results in a product that cannot be readily transferred to other landscapes) [79]. There are also some directed training data acquisition techniques to improve the quality rather than the quantity of data [67, 195]. This would potentially work better in landscapes that have less spectral variety or for questions with a couple targeted classes. Other mechanisms, like using multitemporal and multispectral images, and mixing delineation techniques are being developed [131].

One way in which the visual estimate methods were superior was in the incorporation of firsthand, local knowledge. When making classifications, wetlands are visually similar to both water and to grass. The nuance of the visual difference is based on an understanding of the landscape (where wetlands may be found and when), and the ability to detect a "texture" (the fact that wetlands can have different types of vegetation). When studying wildlife use, being able to detect small wetlands in urban areas, especially in lowland tropical forest such as Amazonia, is fundamental. Wetlands have been shown to be an important predictor of bird diversity in cities around the world, and are, concurrently, one of the most threatened habitats (f. ex. [174, 109, 143, 165, 9]. In Amazonia, where as many as 169 bird species have evolved in wetlands [156, 20], misclassifying or failing to detect wetlands could lead to false conclusions about this group of habitat specialists. These difficulties are well known and improvements are being made to better classify wetlands remotely [131].

2.5.3 Software, access, & implications

Besides the spectral difficulties in image classification for high resolution images described above, there are other institutional and economic considerations specific to the authors. The majority of this project's lifetime was spent identifying and accessing the correct software to attempt these classification methods. Software for analysis of geographic information systems range from open access (QGIS, Orfeo Toolbox, and R) to licensed software (ArcGIS, ECognition, and ENVI). Licensed software can come in a variety of iterations and costs. ArcGIS products span from $100/year (viewing privileges) to $6,000/year (ArcGIS desktop advanced with all extensions). Additionally, the Feature Analyst tool for ArcGIS, which performs better analyses than the Spatial Analyst tool for high resolution imagery [179], is now sold via an external party that does not list the price. The price for ECognition is unavailable online, although a Google search produced an invoice at UT-Austin that priced student developer price from $90/year individual - $7,540 for a perpetual license + trident bundle. ECognition Essentials is, according to their website, 1/4 of the developer cost. In order to access the price for ENVI, you have to have an account. Penn State offers a one-year license for their academic community at $70/year. Neither University of Chicago nor the Universidad Nacional de la Amazonía Peruana has ENVI available. Unless institutions decide to purchase these software packages and the computers that can run them, all of these are largely inaccessible. Furthermore, for subscription-based software, you must have a stable and fast connection to the Internet, which the Peruvian Amazon does not have [57, 130].

As far as open source software, the best platforms on which to visualize and analyze spatial data are QGIS, R, and GeoDa. However, optimum functionality on all three requires either external plug-ins, programming language skills, or both. While the discourse around open source and open access centers itself around democratization, there are studies that show that the majority of open access use is by people who already have the programming skills and access to begin with [111]. While there are efforts to address inequalities through programming education, these are not always effective and often simply recreate the already existing inequalities [101]. There is also a push for making open science more ethical (f. ex., The Open and Collaborative Science in Development Network, the Civic Laboratory for Environmental Action Research, among others), but these are recent initiatives, rather than the norm [142].

These issues with lack of access to technology, and the extension of educational opportunities in the absence of structural political change can have indirect consequences on communities themselves; For example, in Nauta itself, the discourse and expectation around higher education and white-collar jobs has been directly linked to an uptick in youth suicides [29]. Instead of encouraging the use of recently developed technology in academia, social development, conservation, and government, collectively valuing the abilities and technology that people already have, and acknowledging that methods without as many technological requirements are not only cheaper and more accessible, but also in some cases better, would facilitate self-directed growth and governance.

2.6 Conclusion

Through the use of high-resolution satellite imagery, it is now possible to obtain relevant land use information for urban wildlife research questions. In towns and cities poised to be models for sustainable development, like Nauta, Peru, this land use information is paramount for local peoples to ask research questions, and plan and design their city's growth accordingly. Although current literature recommends the use of computer algorithms as the preferred method for image classification, this study shows that visual estimate of satellite imagery by someone with local knowledge is more accurate and easier to implement.

2.7 Acknowledgments

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CHAPTER 3

PEOPLE THINK THERE'S NO NATURE IN CITIES, BUT WANT TO KNOW MORE

3.1 Abstract

We surveyed 963 residents to their knowledge, engagement, perception, and curiosity of bird biodiversity in four Peruvian cities in two different ecosystems (Lima and Huacho in the Pacific desert, and Nauta and Iquitos in the western Amazon). Surveys also included information on social variables such as age, gender, education, activities outside, and years in residence. Bird point counts were carried out in the same sites where residents were surveyed. These sites were also visually assessed for greenspace cover, and distance to nearest landmarks. Exploratory analyses (Principal Components Analyses and Factor Analysis of Mixed Data) were carried out on environmental and survey data to summarize and resulting dimensions in multivariate linear models. Amazonian cities had higher "knowledge" and "engagement" scores than the desert cities. Best performing models predicting "knowledge" scores suggested that urban residents learned about birds outside of the formal education sphere, although there were no strong common patterns among cities or in the full dataset. "Engagement" scores in the desert cities seemed to be linked to local and neighborhood greenspace and education—suggesting socio-economic class plays a role. The overwhelming majority of all four cities' respondents scored highly in "perception" and "curiosity" measures, implying that orientation towards nature is not lost in these four cities and that finding and promoting the human-nature connection in urban areas is a matter of asking the right questions and promoting existing nature practices and perspectives.

3.2 Introduction

As the global population urbanizes, environmentalists and conservation biologists and practitioners have become more interested in understanding the threat of urbanization on nature [163]. Cities encroach on arable land and natural habitat [58], support a human population with a higher demand for meat and other energy-intensive goods [50], and negatively disrupt nitrogen cycling and microbial communities [183]. While creating novel threats, cities can also promote less energy use per capita than rural areas [75], house more people at a higher standard of living than a rural area [2], and present the opportunity to lay down a foundation for a smaller future impact on biodiversity [160]. The route cities take is determined by their residents—a fact that can promote or subvert conservation and environmental priorities depending on the structure of political participation and the attitudes of the resident human population [160].

Human attitudes towards nature are defined by the ways in which people value it. This value is often split into three categories: (1) direct use, that which we gain from using natural resources (this includes many economic and health benefits); (2) indirect use, that which we gain through "ecosystem services" such as climate regulation through forests, and water cleaning through wetlands; and (3) intrinsic/ethical/aesthetic value, that which we gain from the sheer existence of nature [150]. In cities, green spaces can provide direct benefits by promoting exercise [192], providing new economic opportunities for local populations [192], and serving as the setting for urban agriculture [14]. Indirect use of nature in the city is exemplified by trees mitigating the increased temperatures caused by urbanization [108, 51], wetlands purifying water without human intervention for use as tap water [49], and biodiversity providing a plethora of potential hosts for parasites, thus diluting a generalist's potential for infection in humans [78]. In the third category, it is both hard and undesirable to quantify what one gains thanks to life's intrinsic right to exist (since once quantified, one can set thresholds at which to devalue life). What we do know is that the aesthetic quality of nature has promoted scientific literacy through natural history activities like bird-watching

[193], and both green and blue (water bodies) spaces have promoted community development through reported mental well-being and social cohesion [192, 42].

However, many cities are more concrete canyons than urban forests. In these grey spaces, scholars have theorized that humans lose their connection to nature, thus the desire to conserve it, through a process called "the extinction of experience" (Pyle 1978 in [151]). This process states that as the species richness to which humans are exposed decreases, the power of nature to excite humans and incite them into action is lost, whether that action is supporting national parks, or voting for environmentally-friendly political candidates [151]. Limited research into what causes the extinction of experience has been conducted in the U.S, Japan, Spain, Hong Kong, and the U.K., among other countries [24, 167]. Most of this literature is restricted to the global North, while cities in the global South are some of the fastest growing and located in some of the most biodiverse areas [151]. Whether the same patterns of a loss of interest in nature in global South urban residents occur is unknown but is important to identify to provide pathways for peoples' participation in nature conservation and resource management [37].

Here, we present survey results examining knowledge, engagement, perception and curiosity towards birds of resident human populations in four cities of Peru. We chose birds because as a group of mostly diurnal animals present in human environments, they are easy to notice and study, they hold aesthetic and cultural value, and they can indicate environmental health [139, 157]. Given the theory of extinction of experience, we hypothesized that the bigger cities, particularly those in deserts, would have the lowest measures across all response variables. Additionally, within cities, we hypothesized that respondents who live in places with more greenspace and higher biodiversity measures will score higher on all response variables.

3.3 Methods

To assess urban residents' perception, knowledge, and attitudes on birds, as well as factors that may influence them, we collected environmental and biodiversity data at a site level, and socio-demographic data at an individual level.

3.3.1 Study sites & environmental data

City & site selection. We first chose the largest city in two Peruvian ecosystems (Lima in the Pacific Coastal Desert, and Iquitos in the Western Amazon), and then a smaller city about 3 hours away from each large city by highway (Huacho in the Pacific Coastal Desert, and Nauta in the Western Amazon) (see Table 3.1 for general characteristics). Distance assured separation between cities, but proximity and inclusion in the same ecosystem, and difference in sizes assured the possibility of comparison. Sites within cities were selected with the following criteria: >200 m from any other site, <500 m asl, easily accessible by car, and, together, spanning the expanse of the city. Number of sites per city differed due to the difference in size of cities. The distance between sites assured separation, while the inclusion within the same elevational range and representation of city assured possibility of comparison (see 3.1 for city maps).

Table 3.1: Study cities' characteristics. Population from citypopulation.de (in turn, from 2017 INEI Census) [87, 25], except for Iquitos, for which we used the Maynas Province 2007 population estimate. Population growth calculated from the difference between the 2017 population estimate to the 2007 population estimate. Surface area for Lima and Huacho obtained from [64]. Surface area for Nauta and Iquitos calculated on Google Earth as described in chapter 2 of this dissertation. Density calculated by dividing population by surface area.

City	**Environment**	**Population**	**Pop. Growth**	**Surface Area (km^2)**	**Density (pop./km^2)**
Lima	Pacific coastal desert	10,209,275	16.91%	876	11,654.42
Huacho	Pacific coastal desert	141,395	2.55%	31	4,561.13
Iquitos	Western Amazon	404,545	1.58%	36.3	11,144.49
Nauta	Western Amazon	20,716	3.53%	7.5	2,762.13

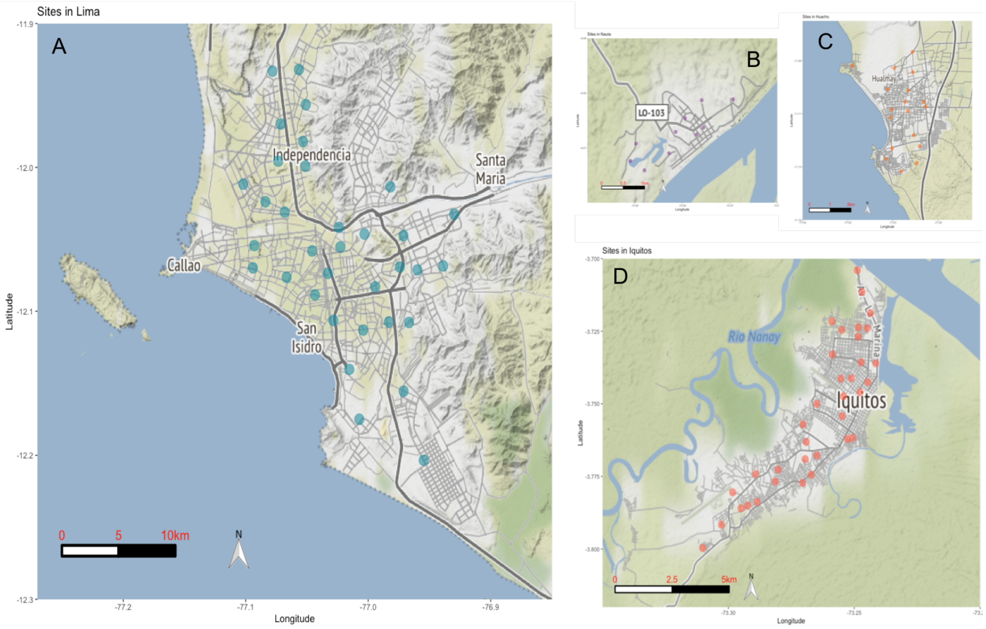


Figure 3.1: Maps of study sites: (A) Lima (scale bar 10 km); (B) Nauta (scale bar 1 km); (C) Huacho (scale bar 2 km); and (D) Iquitos (scale bar 5 km). Maps constructed using R 4.0 in RStudio [153, 158] using the packages ggmap and ggsn [94, 15].

Environmental & bird diversity data. Following the methods described in chapter 2 of this dissertation, we classified each site visually using satellite images acquired from GoogleEarth to characterize both a local and a neighborhood measurement of greenspace and greyspace cover for each site (satellite images used with permission ©CNES/Airbus in 2019, Google Earth V.7.3.2.5776 [1]; Fig. 3.2 demonstrates the local and neighborhood scale). Distance from nearest landmarks (park, center of city, and water) was measured using the distance tool on GoogleMaps. Bird point counts were conducted at every site between January and April 2017 as part of a related project. For this study, we used the following resulting biodiversity metrics: total species richness (number of species seen at each site), average number of individuals (number of individual birds seen at each site averaged across visits), and Simpson evenness (a measure of equitability between species in number of individuals at site, where 1 means that species are all in equal frequency).

Figure 3.2: Examples of the satellite images used to quantify urban land cover. This site is Iquitos Urban Site #33, on the left is the "local" scale, with a radius of 100m, and on the right the "neighborhood" scale, with a radius of 500 m. Satellite images copyrighted to CNES/Airbus in 2019 and downloaded with Google Earth V.7.3.2.5776.

3.3.2 Survey data

Construction. The Knowledge, Perception, and Attitude (KPA) protocol, first developed for public and community health social diagnostics [74], was adapted to assess urban residents' perception, knowledge, and attitudes towards bird biodiversity in their neighborhood (inspired by [38]). Four classes of response variables were chosen (knowledge, engagement, perception, and curiosity) in order to capture more than just knowledge under the Western science paradigm in an attempt to measure multiple ways of connecting with nature [52]. Knowledge was proxied by the ability to identify illustrations of abundant birds in their city (by common, scientific, or popular name—popular names were determined by the sample's most popular response). Selection of birds to identify for each city was determined by the most abundant birds observed during the bird point counts. Engagement with nature was assessed through ownership of pets and gardens, as these have been linked to a higher appreciation of surrounding nature [22]. Perception of biodiversity was approximated by questions focused on a respondents' assessment of their neighborhood's bird community. Curiosity was assessed by asking questions related to a respondent's interest in learning more about birds in their neighborhood.

Surveys also included questions about a respondent's age, gender, level of education, employment, length of residence, their most recent previous residence (if applicable), time spent outside, and types of activities performed outside. These variables, in conjunction with the environmental variables, were candidates for influencing factors in urban residents' attitude with their surrounding nature. Once written, the survey was edited and commented on by three social scientists including two from Lima (Ugarte Villalobos, Andrea; Ugarte Villalobos, Daniela; and Wali, Alaka, personal communication), and approved by the University of Chicago Biological Sciences Division Institutional Review Board (Protocol #IRB18-0045). To access the survey materials, including the illustrated birds and consent language, please see supplementary materials.

Implementation. Between January and April 2018, we surveyed at least ten respondents at every site (total of 97 sites) by going door-to-door or asking people on the street if they lived nearby. Survey respondents were made up of "humans who live at or nearby the bird observation site and spend time there during the day." This audience allows us to relate the survey responses to the site's environmental information. One survey took an average of 5 minutes. There were 6 interviewers for all four cities, with one interviewer (NP) interviewing in all four cities, while the other five were split with three in Iquitos and Nauta (ClP, XV, and EV), and two in Lima and Huacho (MC, and CrP). Once ten people were surveyed at a site, we moved on to the next site. Surveys were carried out between 9 AM and 6 PM. All interviewers were trained together in the study's aims and how to ask questions. Respondents were informed of the study's objective and asked if they consented to taking part. Questions not regarding bird diversity were asked first, while questions on bird knowledge and perception were asked in the same order and after all other questions. In some cases, interviewers wrote down their interpretation of a respondent's gender rather than asking how they self-identify, and as such, all discussion of gender from here on out will be presumed to represent interpretation of gender by interviewer, rather than true gender. If there was a lack of clarity in the question, the question was explained using words not on the survey.

Coding variables. Many responses in the survey were open-ended, and as such required coding for analysis. Employment was coded using the North American Industry Classification System [171]. Information about the respondent's last residency change was coded based on where their last residence was in relation to their current residence ("Movement"). Activities outside were classed into: "Recreation" (activities in which the main objective was to pass time, enjoy the outdoors, or socialize), "Exercise" (activities in which the main objective was to promote physical health), "Extractive" (activities in which the main objective was to consume), "Work" (activities in which the main objective was to produce), and "Other" (activities that do not fall in the prior categories or where the respondent did not elaborate). In cases where people listed more than one, both were counted. In summary statistics, dummy variables were created for each. Topics of interest were categorized broadly by whether the topic was centered on the birds or the human, and whether it related to that focus directly, indirectly, aesthetically, recreationally, or intrinsically. These categorizations are inspired by the human valuation of nature paradigm where nature's value to human society is either due to direct harm or benefit (Direct), indirect ecosystem services (Indirect), aesthetic or cultural meaning (Aesthetic), recreational opportunities (Recreational), or simply by existing (Intrinsic).

3.3.3 Data analysis

All analyses were conducted on R 4.0 and RStudio, using the tidyverse R packages for data wrangling and visualization [153, 158, 189].

Descriptive statistics. Descriptive statistics (minimum, maximum, median, mean, and standard deviation for numeric variables, frequency in percentage for factor variables) were calculated for the full dataset and for each individual city using R package summarytools [41].

Exploratory analyses. Principal component analyses (PCA) were used to summarize the relationships between environmental and biodiversity variables in the full dataset and identify the dimension which best characterizes the "urban" typology. The score on the first principal component was used to characterize each site (from here on, "urban score"). Factor Analysis of Mixed Data (FAMD) was used to summarize and visualize dimensions of attitudes on bird biodiversity by urban residents. Individuals were visualized on FAMD dimensions 1-4 and colored by different potential explanatory variables to visually assess potential factors in influencing the knowledge, engagement, perception, and curiosity scores (from here on out, called the KEPC collectively) of the individual. This was done on the full dataset and by city. All PCAs and FAMDs were run using the R package FactoMineR and visualized using factoextra [106, 96].

Model construction. Multivariate linear regression models were conducted using each FAMD dimensions 1-4 score as a function of the following variables: Age, Gender, Education, Work, Activities Outside, Weekly Hours Outside, Residency Length, Last Move, Observed Species Richness, Average Number of Individual Birds, Urban Score, and Simpson Evenness. Site is not included as a random factor, because the site variables (Observed Species Richness, Average Number of Individual Birds, Urban Score, and Simpson Evenness) deconstruct the site and are hypothesized to be potential factors in determining respondents' KEPC. Outlier individuals (those with unique categorical scores) were excluded from the models. Three sites from Iquitos were excluded because their Simpson evenness bird scores were significantly higher than the rest (0.1-0.4, whereas the mean of the rest of the sites is 0.04 with a standard deviation of 0.01). This pattern seems to be driven in two sites by the lack of flocks of *Brotogeris* spp., result in a more equal distribution in species abundance, and in the third site a low species diversity, n = 3, with consequently more even distribution of individuals). These sites are not outliers in the other metrics. Full dataset models were run with and without the City variable as an independent variable. Models were also run on subsets of the dataset by city. All models used a 10-fold cross-validation as the resampling technique, and stepwise selection. Best performing models within each run were chosen based on the lowest value of root-mean-square-error (RMSE). This work was done using the caret and leaps R packages [115, 100].

3.4 Results

3.4.1 Descriptive statistics

Full descriptive statistics are included in the supplementary materials. There were 963 respondents in the four cities of Iquitos (n=350), Nauta (n=101), Huacho (n=180), and Lima (n=332). Of these respondents, 52.8% of them were recorded as women, and 46.1% were recorded as men (1.15% had no record; within city proportions were 43.6% - 53.3% women, and 43.9% - 56.4% men). The age distribution for all four cities was also comparable (mean ± sd for each city: Huacho 41.3 ± 19.3; Lima 43.5 ± 19.5; Iquitos 40.8 ± 18.5; and Nauta 41.4 ± 16.1), with a combined mean of 41.9 years old and standard deviation of 18.8 years. Respondents in Lima were more highly educated than those in the other three cities with almost 22% having completed university, while in the other three cities this proportion lay between 15-18%. While half of respondents in each city worked in "other services" (mainly domestic labor) or were students, the other half differed according to city size: Huacho's, Lima's, and Iquitos' respondents worked mainly in retail (9.4%, 17.7%, 10.2%, respectively), were retired (9.4%, 9.0%, 2.9%), or worked freelance (Huacho and Iquitos; 6.7%, 10.6%) or in administration & support (Lima, 6.6%). In Nauta, the workforce following other services and students were educators (15.8%) and those who worked in agriculture, forestry, fishing, and hunting (14.9%). Lima, as the biggest and most Westernized city, has more market-based jobs (retail and administration & support) than the other three cities. Nauta's workforce reflects the local economy, which revolves around agriculture, hunting, and fishing, and the fact that the city has schools from primary to post-secondary levels, with a higher proportion of educators and people who work directly with natural resources [68].

These differences between cities are also reflected in the nature of the activities done outside – while in Huacho, Lima, and Iquitos respondents rarely worked outside (7.8%, 3.3%, 7.4% respectively), 14.9% of Nauta respondents identified as working outside. Nauta also seems to be a more transient city with the average years in current residence being 15.1 years, while the other cities were between 18 and 20, and the most movement residents experienced was moving from rural to urban (35.6%), whereas in the other three cities it was within the same city (35% in Huacho, 37% in Lima, and 52.9% in Iquitos). Household movement within Nauta was relatively low (26.7% in city and 2% in the same neighborhood) and this may reflect the relatively recent growth as it positions itself as an important port and connector to Iquitos from the rest of the country [68, 60] (Tab. 3.1). Lima is the only study city whose respondents included international moves (2.4%), showing that significant international communities in these four cities are limited to the capital.

The Amazonian cities, Iquitos and Nauta, had more respondents with gardens and had a higher average number of reported species in their garden than those of the desert cities. Respondents from the Amazonian cities also gave more responses for the bird identification exercise, and on average identified more illustrations correctly than those of the coastal desert cities (Fig. 3.3b-d). Both large cities, Lima and Iquitos, had a higher fraction of pet owners than their smaller counterparts (Fig. 3.4b). Despite these differences, over 90% of respondents (both when combined into the full dataset and when broken down by city) had noticed birds in their neighborhoods (Fig. 3.5b). Over half of respondents (64.1%, with individual cities ranging from 53.2% to 73.6%) believed the biodiversity in their neighborhoods to be low and, on average, estimated about 4 different types of birds occurred in their neighborhood (species richness based on bird surveys varied from 3 to 35 in 87 sites, averaging at about 17 species/site) (Fig. 3.5c-d). Over 70% of total respondents in each of the four cities wanted to know more about birds (Fig. 3.6b). The most popular category of subject matter people wanted to know about birds is “Birds Intrinsic,” a category that made up of information about the birds themselves—e.g., identification, habits, behavior, migration, and evolution.

3.4.2 Exploratory analyses

The full environmental PCA was performed on 97 sites using the following log-transformed traits: percent land cover (at both local and neighborhood scales) of trees, buildings, grass, asphalt, dirt; distance to nearest landmarks of park, water, and center of city; average number of individual birds, Simpson evenness, and species richness. Percent land cover at both scales of water and wetlands were excluded because they did not show normal distributions. Dimension 1 (PC1) suggested an urban gradient, where higher numbers were associated with greenspace and trees and lower numbers with buildings and asphalt (Table 3.2). Dimension 2 (PC2) suggested a gradient of greenspace versus dirt open area. Dimensions 3 and 4 were less clearly interpreted, although they seem to be related to distance from the center of the city (PC3) and distance from the nearest park (PC4). The four cities displayed little differences along PC2, except for Huacho, the smaller desert city. They did however show a progression along the urban gradient with sites in Huacho and Lima tending towards negative PC1 values and more urban characteristics (for example, higher % of building cover), Iquitos sites spread out on the middle of the axes, and Nauta tended towards positive PC1 values and more tree-heavy or grass-heavy sites. The variables measured through bird surveys had less clear associations with the different dimensions. Observed species richness is most strongly associated with Dimension 1 (less urban, more birds), although it has relatively strong associations with the other dimensions as well (more dirt, less species; further away from center, less species; further away from nearest park, more species). Simpson evenness was associated with dimension 1 (less urban, less evenness) and dimension 4 (less urban, less evenness). The average number of individual birds at a site was positively associated with dimensions 1 and 2 (less urban, more individuals; less dirt, more individuals) and negatively associated with dimensions 3 and 4 (closer to center, more individuals; in places closer to parks, more individuals). Individual city PCAs are included in the supplementary materials.

Table 3.2: PCA loadings (rounded to 2 decimal places) for each environmental variable used. All shaded cells correspond to either the two highest or two lowest loadings for respective dimension. Those shaded in green indicate variables associated with "greenspace", in grey associated with "greyspace" or "concrete cover", and in beige associated with "dirt." In parentheses, the percent of variance explained by the respective dimension.

Environmental Variable	**Dim. 1 (31.6%)**	**Dim. 2 (16.5%)**	**Dim. 3 (10%)**	**Dim. 4 (8.7%)**
LOC_Tree	0.31	0.22	0.16	-0.13
LOC_Grass	0.31	0.22	0.14	0.08
LOC_Asphalt	-0.19	0.24	-0.12	-0.39
LOC_Building	-0.35	0.01	-0.28	0.31
LOC_Dirt	0.09	-0.47	0.29	-0.22
NEI_Tree	0.37	0.13	-0.04	0.02
NEI_Grass	0.35	0.03	-0.02	0.12
NEI_Asphalt	-0.23	0.35	0.10	-0.28
NEI_Building	-0.36	0.18	0.09	0.19
NEI_Dirt	0.03	-0.49	0.20	-0.30
Distance from Park	-0.01	-0.34	-0.27	0.43
Distance from Water	-0.22	0.13	0.54	0.14
Distance from Center	-0.02	0.09	0.53	0.32
Observed Species	0.33	0.15	-0.22	0.22
Simpson Evenness	-0.14	-0.08	0.01	-0.24
Avg. # of Individual Birds	0.13	0.20	-0.26	-0.22

The FAMD for all respondents resulted in a first dimension that summarized "knowledge" variables (explains 23.98% of variance), a second dimension that summarized "curiosity" (12.82%), a third dimension that summarized "engagement" (11.31%), and a fourth dimension that summarized "perception" (10.24%) (Table 3.3). Individual respondents' survey responses were mapped onto these four dimensions with 95% confidence ellipses to assess visually whether any of the independent variables (human or environmental) display clustering. The only variable that displayed strong clustering was city membership (see Figs.

3.3-3.6a for differences in score distribution by city). Categories describing a respondent's interest were excluded from this analysis because the large number of potential answers overwhelmed the construction of dimensions. Outlier surveys (surveys whose contribution to the construction of dimensions singularly defined it) were excluded and the FAMD was re-run. The final FAMD included 956 surveys. City-specific FAMD results can be found in the supplementary materials.

Table 3.3: Final FAMD loadings (rounded to 2 decimal places) for each survey response variable. All shaded cells correspond to the three highest loadings for respective dimension. In parentheses, the percent of variance explained by the respective dimension.

Survey Response Variable	**Dim. 1 (23.98%)**	**Dim. 2 (12.82%)**	**Dim. 3 (11.31%)**	**Dim. 4 (10.24%)**
# of Responses (ID)	0.44	0.03	0.05	0.00
Score on ID (Taxonomic)	0.47	0.03	0.05	0.00
Score on ID (Popular)	0.42	0.03	0.06	0.00
# of Categories	0.03	0.48	0.01	0.10
Interest in More Info	0.03	0.44	0.03	0.11
Species in Garden	0.19	0.00	0.34	0.00
Pet Ownership	0.02	0.05	0.18	0.00
Garden Ownership	0.12	0.00	0.44	0.00
Subj. Level of Biodiversity	0.01	0.10	0.01	0.33
Estimated Bird Species	0.03	0.06	0.00	0.17
Perception of Birds	0.00	0.06	0.03	0.39

3.4.3 Best-performing models

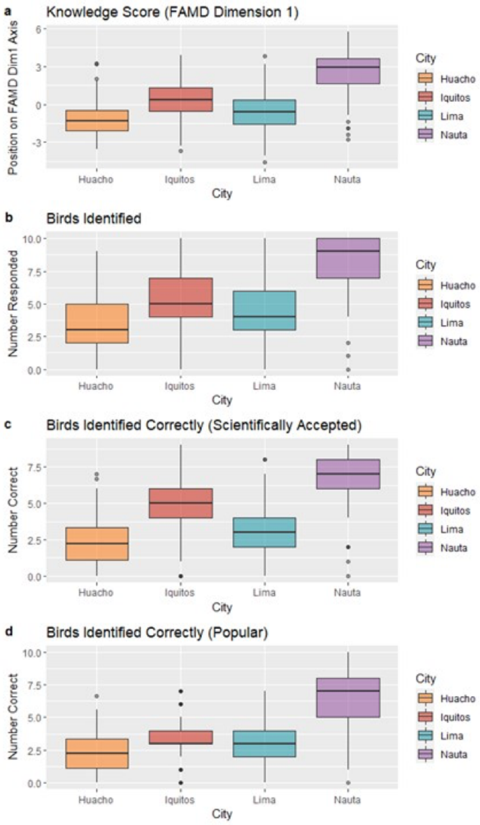
The best performing multivariate linear models were constructed using a dataset that excluded outlier individuals (total respondents = 911; 320 in Iquitos, 101 in Nauta, 317 in Lima, and 173 in Huacho). For each set of models constructed for each response variable, the model with the lowest RMSE was selected for interpretation. Of these, the model with the lowest Bayesian information criterion (BIC) score (-439.94) was the full model, including the city variable, with the response variable as the first FAMD dimension ("Knowledge"; see Fig. 3.3e), and the model with the lowest RMSE was the model for Iquitos where the response variable is the fourth FAMD dimension ("Perception"; see Fig. 3.6e). However, there is not much variation in RMSE amongst all the models presented, and the R2 values never surpass 0.42, with the majority below 0.15 (Figs. 3.3-3.6e).

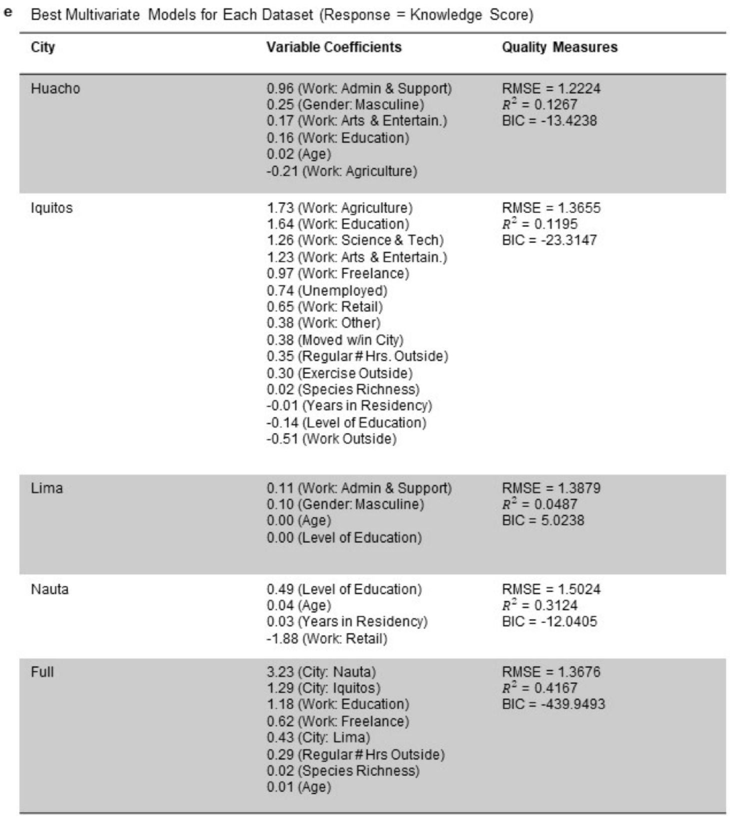
The best models for the response variable "Knowledge" were quite different among cities (Fig. 3.3e): In Iquitos, a variety of work types most strongly affected "knowledge" score (coefficients between 1-2), while working outside and a higher level of education were strong negative factors. Level of education in Lima also had a negative coefficient, although so small that it is likely not largely affecting respondents' knowledge, while in Huacho and in Nauta, working in education was a strong indicator of knowledge about birds. In Huacho, working in agriculture had a negative influence on knowledge of birds. The strongest model for the knowledge dimension was the full dataset, including the city variable. In this model, residency in Nauta or in Iquitos alone was the best predictor of bird knowledge.

When assessing models with the response variable "curiosity score", the strongest negative coefficients are found in work types that require time inside (for example, in the Huacho model, working in manufacturing, or in the Iquitos model, working in administration and support; both with coefficients less than -1.0). The full dataset model is the strongest model if judged by BIC (BIC = -82.05) and supports this idea, where no time spent outside has the strongest negative coefficient (-0.49). However, the distributions of scores and variables show that there are few strong differences in response variables across cities (Fig. 3.4a-c).

Factors predicting score of "engagement" (as measured by ownership of pets and gardens, and garden species richness) differed among cities (Fig. 3.5). In Huacho and Lima, the most interpretable factor is the environmental dimension score: places with a higher "urban score", and thus more green/tree space, are more likely to have residents with pets and gardens. In Iquitos' best performing model, Simpson evenness had the largest coefficient. This coefficient was strongly negatively associated with the engagement score, and may also be a stand-in for an urban score, where a higher Simpson evenness score suggests less species richness and a higher amount of greyspace. In Nauta, being a student made you more likely to have a pet or a garden—yet this does not give us much information as we do not know who in the family made the choice to have a pet or a garden. This did not seem to connect to age, further suggesting that the "student" variable is not the driving pattern.

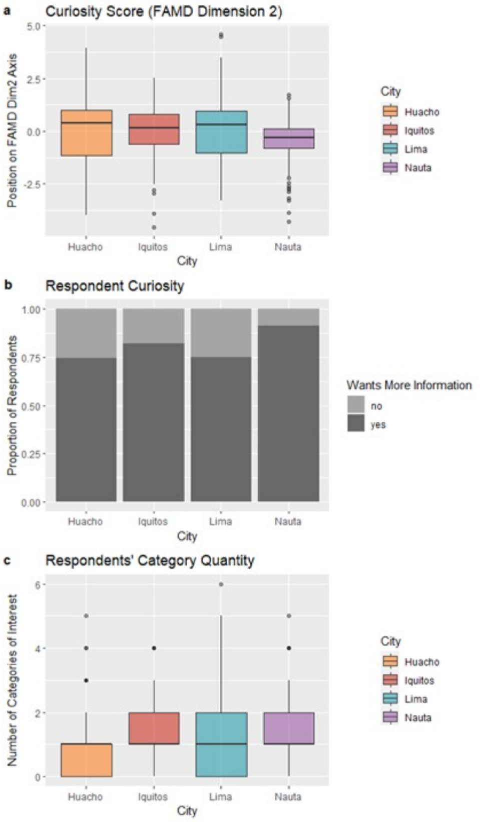
Finally, the best performing multivariate models for the fourth FAMD dimension score ("Perception") are of very low quality (at most explaining 9.4% of the variance, see R^2 of the Lima model, Fig. 3.6). The strongest coefficient was from Nauta where people working in the Science & Technology sector had a positive association (2.58). The strongest negative association was being from the city of Nauta in the full dataset. There were no common factors found between the five models.




e Best Multivariate Models for Each Dataset (Response = Knowledge Score)

City	Variable Coefficients	Quality Measures
Huacho	0.96 (Work: Admin & Support) 0.25 (Gender: Masculine) 0.17 (Work: Arts & Entertain.) 0.16 (Work: Education) 0.02 (Age) -0.21 (Work: Agriculture)	RMSE = 1.2224 R^2 = 0.1267 BIC = -13.4238
Iquitos	1.73 (Work: Agriculture) 1.64 (Work: Education) 1.26 (Work: Science & Tech) 1.23 (Work: Arts & Entertain.) 0.97 (Work: Freelance) 0.74 (Unemployed) 0.65 (Work: Retail) 0.38 (Work: Other) 0.38 (Moved w/in City) 0.35 (Regular # Hrs. Outside) 0.30 (Exercise Outside) 0.02 (Species Richness) -0.01 (Years in Residency) -0.14 (Level of Education) -0.51 (Work Outside)	RMSE = 1.3655 R^2 = 0.1195 BIC = -23.3147
Lima	0.11 (Work: Admin & Support) 0.10 (Gender: Masculine) 0.00 (Age) 0.00 (Level of Education)	RMSE = 1.3879 R^2 = 0.0487 BIC = 5.0238
Nauta	0.49 (Level of Education) 0.04 (Age) 0.03 (Years in Residency) -1.88 (Work: Retail)	RMSE = 1.5024 R^2 = 0.3124 BIC = -12.0405
Full	3.23 (City: Nauta) 1.29 (City: Iquitos) 1.18 (Work: Education) 0.62 (Work: Freelance) 0.43 (City: Lima) 0.29 (Regular # Hrs Outside) 0.02 (Species Richness) 0.01 (Age)	RMSE = 1.3676 R^2 = 0.4167 BIC = -439.9493

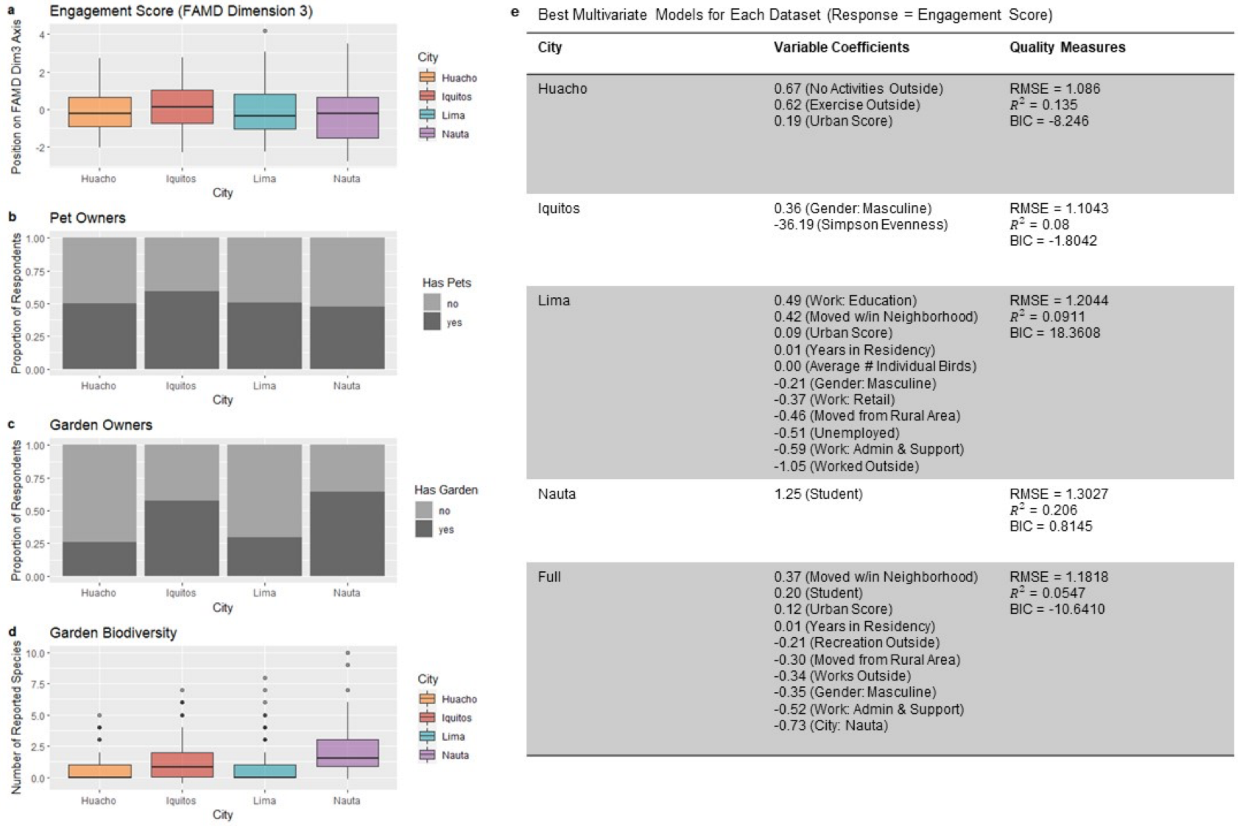
Figure 3.3: Results for "knowledge" response variables: (a) Boxplots for FAMD Dimension 1 score by city; (b) Number of birds responded on bird identification survey by city; (c) Birds identified correctly when graded according to either an "accepted" common name or a scientific name; (d) Birds identified correctly when graded according to the most popular name given; and (e) Best performing models for each dataset (Huacho, Iquitos, Lima, Nauta, and the full combined dataset) with variable coefficients and quality measurements (RMSE, R2, and BIC).



e Best Multivariate Models for Each Dataset (Response = Curiosity Score)

City	Variable Coefficients	Quality Measures
Huacho	0.26 (Level of Education) -0.03 (Age) -0.81 (Work: Retired) -1.71 (Work: Manufacturing)	RMSE = 1.2353 R^2 = 0.2266 BIC = 27.8812
Iquitos	0.50 (Exercise Outside) 0.20 (Level of Education) -0.01 (Age) -1.01 (Work: Admin & Support)	RMSE = 1.153 R^2 = 0.1302 BIC = -26.1836
Lima	0.67 (Student)	RMSE = 1.3202 R^2 = 0.0601 BIC = -0.1525
Nauta	0.03 (Age)	RMSE = 1.0214 R^2 = 0.1421 BIC = -4.3257
Full	0.56 (Work: Education) 0.14 (Level of Education) 0.01 (Average # Bird Individuals) -0.02 (Age) -0.46 (Moved w/in Neighborhood) -0.47 (City: Nauta) -0.49 (No Hours Outside)	RMSE = 1.217 R^2 = 0.121 BIC = -82.0451

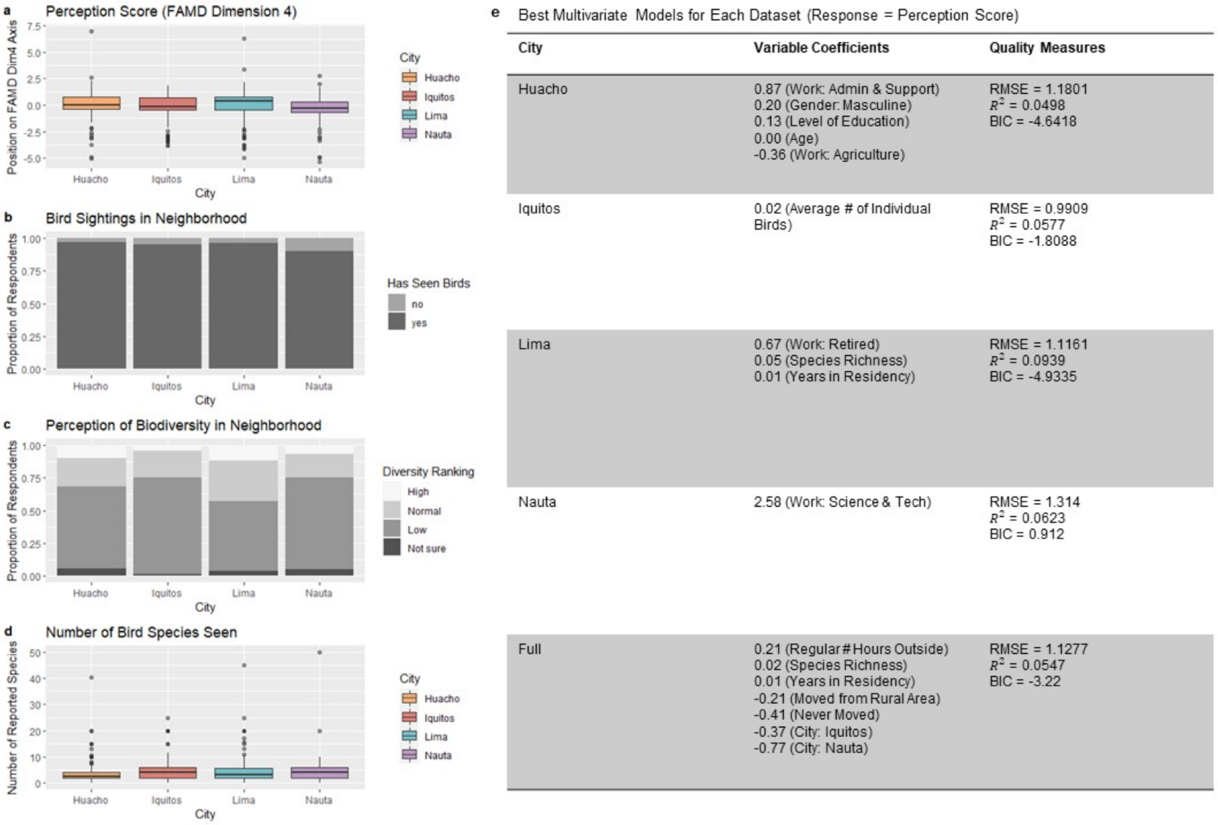
Figure 3.4: Results for "curiosity" response variables: (a) Boxplots for FAMD Dimension 2 score by city; (b) Proportion of residents interested in learning more about birds; (c) Number of categories respondents' answers on what they'd like to learn about birds fell into; and (e) Best performing models for each dataset (Huacho, Iquitos, Lima, Nauta, and the full combined dataset) with variable coefficients and quality measurements (RMSE, R2, and BIC). (d) was skipped for ease of comparison across figures.



Best Multivariate Models for Each Dataset (Response = Engagement Score)

City	Variable Coefficients	Quality Measures
Huacho	0.67 (No Activities Outside) 0.62 (Exercise Outside) 0.19 (Urban Score)	RMSE = 1.086 R^2 = 0.135 BIC = -8.246
Iquitos	0.36 (Gender: Masculine) -36.19 (Simpson Evenness)	RMSE = 1.1043 R^2 = 0.08 BIC = -1.8042
Lima	0.49 (Work: Education) 0.42 (Moved w/in Neighborhood) 0.09 (Urban Score) 0.01 (Years in Residency) 0.00 (Average # Individual Birds) -0.21 (Gender: Masculine) -0.37 (Work: Retail) -0.46 (Moved from Rural Area) -0.51 (Unemployed) -0.59 (Work: Admin & Support) -1.05 (Worked Outside)	RMSE = 1.2044 R^2 = 0.0911 BIC = 18.3608
Nauta	1.25 (Student)	RMSE = 1.3027 R^2 = 0.206 BIC = 0.8145
Full	0.37 (Moved w/in Neighborhood) 0.20 (Student) 0.12 (Urban Score) 0.01 (Years in Residency) -0.21 (Recreation Outside) -0.30 (Moved from Rural Area) -0.34 (Works Outside) -0.35 (Gender: Masculine) -0.52 (Work: Admin & Support) -0.73 (City: Nauta)	RMSE = 1.1818 R^2 = 0.0547 BIC = -10.6410

Figure 3.5: Results for “engagement” variables: (a) Boxplots for FAMD Dimension 3 score by city; (b) Proportion of residents that were pet owners by city; (c) Proportion of residents that were garden owners by city; (d) Number of species reported in their gardens by city; and (e) Best performing models for each dataset (Huacho, Iquitos, Lima, Nauta, and the full combined dataset) with variable coefficients and quality measurements (RMSE, R2, and BIC).



Best Multivariate Models for Each Dataset (Response = Perception Score)

City	Variable Coefficients	Quality Measures
Huacho	0.87 (Work: Admin & Support) 0.20 (Gender: Masculine) 0.13 (Level of Education) 0.00 (Age) -0.36 (Work: Agriculture)	RMSE = 1.1801 R^2 = 0.0498 BIC = -4.6418
Iquitos	0.02 (Average # of Individual Birds)	RMSE = 0.9909 R^2 = 0.0577 BIC = -1.8088
Lima	0.67 (Work: Retired) 0.05 (Species Richness) 0.01 (Years in Residency)	RMSE = 1.1161 R^2 = 0.0939 BIC = -4.9335
Nauta	2.58 (Work: Science & Tech)	RMSE = 1.314 R^2 = 0.0623 BIC = 0.912
Full	0.21 (Regular # Hours Outside) 0.02 (Species Richness) 0.01 (Years in Residency) -0.21 (Moved from Rural Area) -0.41 (Never Moved) -0.37 (City: Iquitos) -0.77 (City: Nauta)	RMSE = 1.1277 R^2 = 0.0547 BIC = -3.22

Figure 3.6: Results for "perception" variables: (a) Boxplots for FAMD Dimension 4 score by city; (b) Proportion of residents that had seen birds in their neighborhood; (c) Proportion of residents that perceived categories from low-high of biodiversity; (d) Number of species estimated in their neighborhoods; (e) Best performing models for each dataset (Huacho, Iquitos, Lima, Nauta, and the full combined dataset) with variable coefficients and quality measurements (RMSE, R2, and BIC).

3.5 Discussion

"Extinction of experience" leads us to believe that residents of big cities, regardless of where they are, have fewer opportunities to interact with nature, and thus have lower scores across measures of knowledge, engagement, perceptions, and curiosity (KEPC) towards nature. However, we show that urban residents' KEPC across these four Peruvian cities may depend more on the socioenvironmental context of the city they reside in than on the size of it. Urban residents in the Pacific coastal desert have lower knowledge scores than urban residents in the western Amazon, yet the best predictive models in each city differed. Likewise, urban residents in the desert have lower engagement scores than those in the Amazon—but the scores for residents in the desert seem tied to availability of greenspace. "Perception" scores are low across all four cities, although the Amazon cities have lower scores, yet "curiosity" scores are high across all four cities. Together, these results show that the possibility of urban human-nature connections, grounded in the city in which people live, exists.

3.5.1 Urban residents in the western Amazon know more about birds

Formal education has been thought to predict scientific and natural history literacy [114, 38], yet urban residents from the Pacific coastal desert consistently scored lower along the "knowledge" axis and variables than urban residents from the western Amazon despite having more formal education (Fig. 3.3), suggesting that formal education, at least in the Pacific coastal desert, does not influence whether urban residents can identify local birds. The best predictive model for the full dataset identified residence in Nauta or Iquitos as the strongest predictive factor for high "knowledge" score (Fig. 3.3e). Residents from these cities also consistently scored higher in the bird identification exercise, despite having less formal education than those of the desert cities. This points to a stronger extracurricular environmental awareness—the department of Loreto's economy, like the rest of the Amazon's, revolves around its natural resources, of which birds provide an attractant for tourism and

Iquitos and Nauta are points of access [60], while in the department of Lima, Huacho and Lima are industrial and commercial centers [181, 105]. Results from Lima and Huacho show similar knowledge results to those found in Santiago, Chile, another capital city in a similarly arid, albeit higher elevation, ecosystem [38].

3.5.2 Urban residents in Pacific coastal desert cities own gardens and pets as long as there's water and greenspace

Engagement scores for the Pacific coastal desert cities indicate that socioeconomic factors are more important there than in the Amazonian cities, where residents had more gardens with more garden species more consistently (Fig. 3.5c-d). The overall predictive model identified a high urban score (more green/tree space) as a positive factor in determining engagement score, yet the city-specific models differed in the role of the environment versus demographic factors (Fig. 3.5e). In Lima, the best model identified unemployment and moving from rural area as negative factors—two factors that are indicative of low socioeconomic class in the nation's capital. From a resources perspective, this makes sense: Water access constrains the ability to have a garden, and water access (and more greenspace) is linked to higher socioeconomic levels [88, 17, 137]. Water access for plants may not be as linked to higher socioeconomic levels in the Amazon where high levels of rain and the surrounding wetlands make water for gardens easily accessible for all. This is supported by the fact that non-environmental coefficients in the models for Iquitos and Nauta are low (Fig. 3.5e). Simpson evenness however had a very high coefficient in Iquitos, and could function as a potential proxy for how urban a site is given that higher Simpson evenness score suggests a lower species richness and a lower amount of greenspace—and thus less space or water for a garden or a pet.

These measures as quantifying engagement with "nature" may fall apart because the assumptions of what they measure come from another part of the world. What it means to have a garden or a pet is defined culturally, and what it may mean in one part of the world may not mean the same thing in another. For example, some people when asked if they had a pet would say no, but would later mention that they feed stray animals. Another example is that our questionnaire used the word "*jardín*", when this word has a connotation of flower garden, rather than "*huerta*", which suggests a vegetable or fruit garden. We quickly incorporated "*huerta*" into the conversation we had with respondents while implementing the survey—however, this may also suggest that these percentages are underestimates of garden ownership in our study cities. Additionally, the concept of having a home garden may be inapplicable to a context in which some urban residents still tend to rural fields (*chacras*) as may be the case in at least three of the four cities (Huacho, Iquitos, and Nauta). Anecdotally, there were some respondents, especially in Nauta, that would say they did not have gardens, but then told us about their chacras outside of town.

Despite these limitations, respondents in our Amazonian cities (Iquitos 57.7% and Nauta 64.4%) had much higher percentages of gardens than those in reported global North cities such as Stockholm, Sweden (16%), and Dunedin, New Zealand (19-27%), which were more similar to the percentages of reported garden ownership in Lima (29.5%) and Huacho (26.4%) [44]. Neither Dunedin nor Stockholm are in deserts, suggesting that although water access and environment may play a part in these differences, so does culture and socio-geographic position. Culture and socio-geographic position also influences how we interpret our results: For example, having property in both rural and urban areas is usually a mark of a higher socioeconomic class in the global North: People have to have enough wealth to purchase and manage two properties [125, 172]. This is not necessarily the case in the global South, where there are still prevalent concepts of community ownership and family connectivity along the rural-urban gradient, land ownership can be acquired through settlement rather than purchase (including in urban areas), and property taxes are not high or enforced [26, 145, 53]. Therefore, ownership of garden or pets and whether it relates to engagement with nature depends on which city and where in that city you live.

3.5.3 Urban residents' perception of bird biodiversity in their city may also depend on ecosystem

Residents in all four cities perceived their neighborhood's biodiversity as low, yet the proportion of residents per city is higher in the Amazon than in the Pacific coastal desert (Fig. 3.6b-c), suggesting that how urban residents perceive their neighborhoods' biodiversity is a function of context. Cities are less biodiverse than their surroundings and cities' biodiversity are more similar to each other than to their surroundings [123, 13, 168], but this does not mean that cities are devoid of biodiversity or that they are always less biodiverse than their surroundings (Piland, unpublished data). In some cities, the input of energy and resources by humans supports more individual birds [119], and this seems to be the case in Lima, where the average number of individual birds per site (41.07 ± 29.1) was higher than Huacho (35.72 ± 17.5) or Iquitos (34.5 ± 11.7). In Nauta, the average number of individual birds per site is 50.04 ± 23.8 and may still be relying on a mixture of urban and rural resources (a situation hypothesized with theoretical models, [7]).

In the Amazon, cities' surroundings are some of the most bird speciose in the world—in comparison, the cities themselves are species-poor. In the Pacific coastal desert, the surroundings are less speciose than those in the Amazon, as such, the cities have similar amount of birds and sometimes more (see chapter 4 of this dissertation). In our study, we registered a range of 3 species in one site in Iquitos to 35 species in another site in Iquitos, and a mean species richness ranging from 11.5 species/site (Huacho) to 23.9 species/site (Nauta). Yet, a higher proportion of people in Nauta and Iquitos categorized their neighborhood as having "Low" biodiversity.

3.5.4 Urban residents across the board want to know more about birds

In all four cities, over 75% of respondents wanted to know more about the birds in their neighborhoods (Fig. 3.2). From the group of residents that were interested in learning more about the birds in their neighborhoods, the majority were interested in information about birds themselves. The second most popular general category of response differed by region: those of the coastal desert were most interested in information about how birds relate to humans directly (how to keep them as pets or raise them, whether they transmit diseases, etc.; about 16% for both cities), while in the lowland rainforest, respondents were interested in information about what supports or interacts with the birds (in particular, their habitat, their ecological relationships, etc.; ˜17% in Iquitos and ˜13% in Nauta). After these three categories, the most popular category for all four cities was information for information's sake. Many respondents said they would be interested in learning more simply because it is always good to know more.

This suggests that although urban areas may diminish the opportunity to spend time in places considered to be "natural", it does not diminish the ability to perceive, be interested in, and be motivated to interact with natural elements (in these cities, with birds), or, what is called "orientation." This aspect has been shown to be more important than "opportunity" in other cities (such as in Brisbane, Australia [107]), and has been theorized to be another casualty of urbanization, a driver of "extinction of experience" [167]. Yet, the belief that orientation is lost in urban residents may be an issue of study design, where researchers ask questions that do not get at specific urban residents' orientation.

Bias in research design as it pertains to human perception of, connection to, and involvement with nature is well documented. In the United States, there is a long-standing idea that because Black people and non-Black people of color (POC) in the United States are not highly visible in the environmental movement, they do not care about the environment [176]. This idea is supported by researchers asking the wrong questions to assess people's connectedness to nature [52]. Connectedness to and willing to act in the interest of nature has been measured using: the Connectedness to Nature Scale (e.g. [121, 141]; visits, hiking, and backpacking in parks (e.g. [198, 194]), and knowledge of Linnaean classifications of wildlife (e.g. [43, 38]). Yet, the Connectedness to Nature Scale has been shown to be biased and in-effective [147, 199]. Asking about visits to protected parks in the United States prioritize the experiences of white people, given that many were historically only open and or accessible to them [31, 192, 138], and that U.S environmentalism was founded on Native displacement, land-grabbing to keep Black people from owning property, and xenophobic policies to keep these portions of the population down [128]. Knowledge of Linnean classifications assess only one type of identification of wildlife that has a history of being inaccessible to those outside groups of power, and emphasizes an individual whose original classifications included racist characterizations of humans [23, 169, 52].

In the global South, the stereotype is that nature is not an urgent enough matter for indigenous people, Black people, non-Black POC, and/or the poor [55, 118]. Pyle himself, in 2003, wrote about how in the global South, the extinction of experience is even more dangerous because urban communities are poorer and therefore cannot have the luxury of time to care about the environment [151]. Thus, much of international cooperation is oriented towards economic livelihood initiatives such as REDD+ or certified sustainable/fair-trade agriculture [126], as though the only way people in the global South could care about the environment is if there is an economic incentive. Yet, many urban areas are made up of these communities, and research and personal experiences show that this perceived lack of concern, both in the United States and internationally, is not true (e.g [55, 70, 73, 146]).

In our study, we show that residents in all four of our study cities perceive and are interested in birds across neighborhoods (with different socioeconomic, cultural, and racial histories). The fact that urban residents are most interested in information about the birds themselves rather than how to capitalize on them shows that there are other non-monetary benefits that nature (birds, in this case) may have on urban residents of, at least, these cities in Peru (for more information on potential benefits that are outside the scope of this work, see [120]). Supporting these already existing orientations, while attempting to act more as a translator between different economies and politics rather than as a “change agent”, can empower community participation in politics, self-determination, and ultimately environmental management and stewardship [182].

3.5.5 The possibility of an urban human-nature connection

Taken together, the questions asked in our survey show that urban residents learn about birds in multiple ways, engage with nature in a context-dependent way, and overwhelmingly perceive and are interested in birds. This suggests that being connected to and interacting with one's environment and noticing who or what lives in it is a fundamental necessity for survival, and dichotomies between "human" and "nature" are false. The idea that this connection would be severed by a social construct based on racial phenotype, ethnic or cultural subgroup, socioeconomic class, or urban/rural residency is presumptuous: instead of asking whether or not groups are connected to nature, we should be asking how different groups connect to nature.

Additionally, our research runs counter to literature that prescribes a focus only on children to prevent the extinction of experience as a long-term investment [127], and because they have the strongest possibilities in creating a connection to nature [40]. During survey implementation, many survey respondents of all ages went on to engage in a conversation to suggest ideas on how to engage residents in noticing and learning about neighborhood birds. One respondent from Lima was very excited to think about ways to involve their child—they mentioned puppet shows about birds at the park, interactive activities at the park, and creating local field guides. Adult respondents in all four cities shared many thoughts and questions on birds that were hard to categorize within this context. Some of these questions included: "Why do we not have the lions and tigers that we see on TV? Why are the birds that we see here not on TV?"; "Do the birds sing because they're sad?". The focus on children is important, but children do not exist in a vacuum, they interact with adults, who themselves, can communicate their connection to nature [162]. Harnessing the excitement of the parents and other adults is beneficial, not just in engaging in a larger conversation and answering questions together, but also for society. The idea that things change over generations is one that is true, but also limiting, shouldering the responsibility on the next generation to change when we can start creating a more environmentally and socially just society now [36].

The environmental movement's romanticizing of "wildness" and "pristine" landscapes have painted a picture of nature that is inaccessible for many urban residents and fomented the idea of "extinction of experience" in urban areas [46, 151]—if not because they cannot afford to take time off and go to potentially dangerous rural areas, then because it simply does not exist. For example, most natural areas, such as the contiguous forests of the Amazon, are the settings in which humans have and continue to evolve, and they have been formed by this relationship [80]. In The Nature of Cities, Dr. Marianne Krasny writes of her surprise at the strength of the connection to nature she felt in the Lower East Side of Manhattan [99]. Instead of feeling this connection from the sight of a pristine alpine landscape, or a wild oceanic wave, she feels it from meeting a family working a community garden. She continues to reflect: "In preventing 'extinction of experience', it is necessary to define what the experience you're preserving is." From the data we have presented, it is clear that residents in these communities are noticing and are interested in nature—as conservation professionals, our role could lay in connecting residents to those who may support their initiatives, financially, politically, or technologically, and, as residents, our role could lay in engaging with our communities.

3.6 Conclusion

Environmental characteristics, bird diversity metrics, and resident surveys were assessed for multiple sites across four Peruvian cities to study urban knowledge, engagement, perception, and curiosity towards birds. In the light of the theory of extinction of experience, we expected to see patterns of loss of KEPC and thus a growing indifference as cities and neighborhoods become more urban. However, while knowledge and engagement (garden and pet ownership) did generally decrease from smallest city to largest city, the complexity and diversity of the best performing models suggest interactions between the city's natural and social history and its present. Perception and curiosity measurements stayed broadly constant across cities, underlining that urban environment itself may not be definitive of people's disconnection to nature. This study suggests that judgments of people's connection to nature may be a function of the questions asked rather than the actual connection to nature. It suggests that in order to promote connection to nature in our cities we should engage with our communities, building relationships to collaboratively organize and create spaces of and avenues to connection, and, if we work outside of our place of residency, initiatives should be defined and lead by the people who live there.

3.7 Acknowledgments

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CHAPTER 4

SPECIOSE PLACES LOSE DISPROPORTIONATELY MORE DUE TO CITIES

4.1 Abstract

High biodiversity tends to lead to greater ecological function, yet it is unclear whether this protects vulnerable species from anthropogenic change. Given the discourse around biodiversity conservation, it is important to understand the connections between diversity and species vulnerability. To characterize species vulnerability we use an index proposed to reflect the theoretical probability of extinction due to organismal traits and the IUCN threat status. Using avian trait datasets and citizen science datasets, such as eBird, we these relationships within a comparative framework, addressing three questions: (1) Do assemblages with higher species richness have proportionately more vulnerable species? (2) Do assemblages with higher species richness proportionally lose more species? And if so, (3) Do they lose vulnerable species first? By comparing avian urban and rural assemblages' vulnerability-species richness associations in 37 cities along across Latin America, we find that more speciose assemblages do lose more species, proportionally, than less speciose assemblages. However, our results show that assemblages with higher regional species pools do not consistently have more vulnerable species (by vulnerability score or by IUCN threat status level). Assemblages with higher species richness can, however, support individual species with a higher IUCN threat status than assemblages with lower species richness. These results suggest that conservation measures that prioritize full assemblages continue to be relevant in the protection of critically endangered, endangered, and vulnerable species.

4.2 Introduction

High biodiversity tends to lead to greater ecological functioning by more efficiently capturing biologically essential resources resulting in higher biomass [35]. Additionally, biodiversity confers important properties to these systems that could prevent species loss, including greater stability of function, resistance to invasive species, and reduced rates of disease transmission ([77, 178], among others). These same ecosystem functions are important to human —biodiversity has been shown to have a great effect on the biogeochemical and climactic properties of the globe [35, 134]. Despite the correlation between species diversity and function, the connection between biodiversity and the vulnerability of assemblages in the face of anthropogenic change is still debated [35].

Theoretical and experimental approaches to this problem transformed species richness, as a measure of biodiversity, from a dependent variable in study design into an independent variable, highlighting that species richness is not only a product of function, but an important factor [113, 112]. This has also been borne out in natural systems [84]. More diverse assemblages tend to be characterized by higher levels of niche partitioning [180] and functional complementarity [112], and a greater number of interactions (termed ecological complexity, [4], often through competitive interaction [5]). These characteristics result in greater stability (defined here as less variance in biomass and less variance in diversity measurements in the face of disturbance [**?** 35, 178]), despite the fact that these food webs, competitive networks, or functional space may be dominated by one or one type of organisms [35, 178].

While diversity may increase the resilience and resistance of assemblages in experimental and short-term settings, understanding the impacts of biodiversity and ecosystem function relationships in natural systems has been limited. There is some evidence, for example, that more species rich communities may accumulate species with traits that ultimately make them more vulnerable to extinction, making diversity—paradoxically—increase vulnerability through evolutionary time [186]. Further, different dimensions of diversity can have different relationships with function: for example, species diversity of vegetation may have a positive relationship to the quantity of vegetation exposed to herbivory, while phylogenetic diversity may have a negative relationship to the quantity of vegetation exposed to herbivory [133]. Here, the mechanisms linking these dimensions of diversity to function differ [66, 35, 133]. The mechanisms can change over time [104], and be impacted by historical contingency [186].

While there is evidence that biodiversity and ecosystem function dynamics can influence extinction risk in complex ways, our understanding of these relationships in natural systems remains limited. This is because conducting empirical research on this topic is difficult due to the multitude of factors that may affect an assemblage's, and its species', survival in the real world : extinction may result from many different anthropogenic drivers (e.g. land-use change or harvesting) [89], and intrinsic biological properties may make anthropogenic factors more dangerous (e.g. body size, rarity) [19, 155]. Large-scale functional trait datasets (e.g. [190, 148, 164]) make it possible to tease apart these factors using comparative methods.

Urbanization presents a major threat to many species. Urbanization has similar characteristics regardless of location: it is defined by impervious surfaces, a dense human population, and limited and fragmented greenspace [122]. The recent rise in urban ecology and evolution studies has been able to show that many of its patterns may be global; however, generalized research in the tropics is still lacking (see reviews: [144, 122, 92]; however, some in-country comparative studies exist, see [72] for one Mexican example). Thus, understanding how urbanization affects ecosystems in the most speciose regions is an important contribution to conservation [135, 168].

In this study, we address three questions: (1) Do assemblages with higher species richness have more vulnerable species? (2) Do assemblages with higher species richness proportionally lose more species? And if so, (3) Do they lose vulnerable species first? We characterize differences in urban and rural avian diversity for 37 cities across a latitudinal gradient in Latin America to understand whether diversity per se influences diversity loss as a consequence of urbanization. Additionally, we test whether changes in diversity affect assemblage vulnerability and IUCN mean threat status in predictable ways. Finally, we test whether species-specific vulnerability or IUCN status predicts their persistence or loss in urban settings. This work links assemblage- and species-level approaches to characterizing vulnerability and tests their predictive power in anticipating assemblage diversity and vulnerability in cities for the first time across Latin America.

4.3 Methods

4.3.1 City selection

Cities were selected by filtering the Global Human Settlement dataset [64] to cities in the“Latin America & Caribbean” region. Limiting cities to this region is a coarse approach to controlling for differences in sociopolitical history that influence aspects of the urbanization process [110]. A “city” is commonly defined as a populated area with a population of at least 100,000 people [10, 64] and we adopt this definition here (using population sizes for 2010). Latin America & the Caribbean is also among the most species-rich regions in the world, particularly for avifauna [149], and among the most urbanized [76], creating a situation where cities have caused dense recent land-use change within highly diverse natural ecosystems. In QGIS, we created two buffer zones around each urban polygon at a distance of 10 km from the urban boundary and between 10 and 50 km [152]. We generated species lists for these polygons using eBird checklists. We only used “complete” checklists (i.e. observers self-reported that they marked every bird they saw or heard), checklists from outings that lasted less than 12 hours, covered an area less than 5 km^2 or a transect less than 10 km, had fewer than 10 observers, and were identified as the primary group checklist [93]. Cities were then filtered to those that had ten unique sampling days per city-buffer combination, following [191], using the ‘auk’ [173] and ‘tidyverse’ [189] packages in R [153].

4.3.2 Community matrices

eBird observations were organized into community matrices, where each row is one checklist, each column is a species, and each cell is a presence observation. Subspecies and observations labeled “domestic” were summarized into their species category (including those considered full species by eBird, reference taxonomy is [91]). Birds identified to genus but not to species were assigned to the most common species in that genus for that city-buffer combination. Identifications at family or order level were excluded from the matrix. Summary community matrices for each city-buffer combination were then created. Species for which a single individual was reported on a single checklist (singletons) were removed from the community to lower the probability of including misidentified species or vagrants, and, instead of using abundance, we used incidence frequencies (number of checklists in which a species appears/number of checklists total) for each city-buffer combination. In combination with those described in the previous section, these filtering techniques create a conservative dataset for community matrices for each city-buffer combination, approximating a “core” assemblage at each location.

4.3.3 Rarefaction for species richness and species lists

Species richness for each city-buffer combination was estimated using sample-based rarefaction where each checklist considered to be one sample, using the ‘poolaccum’ function in the vegan package [140] in R to conduct 1,000 permutations [140]. At each draw, the bootstrap estimator for species richness was calculated to calculate the accumulation curve. We used the rarefied species richness for 10 checklists (minimum number of checklists accepted for inclusion). Each “core” assemblage was then truncated to the rarefied species richness number according to highest incidence frequency (for example, if a city-urban combination has 180 species based on 50 checklists, but 100 based on 10 checklists, the 100 most frequent species were considered part of the final rarefied “core” assemblage). Regional species pools were then defined by all species occurring in any of the three rarefied “core” assemblages (urban polygon, inner buffer 0-10 km, and outer buffer 10-50 km).

4.3.4 Assemblage vulnerability

Assemblage vulnerability was quantified using species vulnerability scores based on species extinction probability [186]. For each species, a vulnerability score was calculated based on intrinsic biology ($\mathrm{V_s(T)}$, where s means species of interest, and T stands in for the relationship between traits that affect V or vulnerability). This was the unweighted mean of clutch size, body mass, and the inverse of dispersal:

$$\mathrm{V_s(T)} := \frac{1}{3} \cdot (\text{-}\mathrm{z_{clutch\ size}} + \mathrm{z_{body\ mass}} - \mathrm{z_{dispersal\ ability}}).$$

Each trait that went into this species vulnerability score was standardized using z-scores. As such, a species with a high $\mathrm{V_s(T)}$ would be more vulnerable to extinction than a species with a low $\mathrm{V_s(T)}$ [186]. $\mathrm{V_s(T)}$ was calculated for each species represented within the species dataset by creating a trait dataset that included published literature on clutch size [90], body mass [56, 190], and dispersal ability (as approximated by hand-wing index; [164]) . For any species not included in the references listed (41.07% of species for clutch size; 2.55% of species for hand-wing index; and 2.13% of species for body mass), the data was pulled from a different source in this order: (1) the Handbook of the Birds of the World (accessed via the virtual Birds of the World [21]); (2) direct measurement of 3-4 museum specimens (only applicable for HWI; measurements done at the Field Museum of Natural History, the American Museum of Natural History, and the California Academy of Sciences); (3) data from the nearest sister taxon [91]; (4) an average of the available data for its genus; (5) an average of the available data for its family; and finally, (6) an average of the available data for its order. Z-scores were then calculated for each species to standardize across variables, resulting in a $\mathrm{V_s(T)}$ for each species. Using the Pearson's test, correlation between clutch size and body mass was 0.29 ($P < 0.005$), between clutch size and hand-wing index was 0.01

(P = 0.59), and between mass and hand-wing index was 0.06 (P <0.005). The vulnerability of an assemblage was then calculated as the mean species vulnerability scores for all species found in the assemblage (rarefied species lists for urban polygons, and full regional species pool for regional).

4.3.5 IUCN mean threat status

IUCN status for each species in the full dataset was obtained from their website [89]. Status for each species was then converted into a numerical number, such that least concern equals 1, near threatened equals 2, vulnerable equals 3, endangered equals 4, and critically endangered equals 5. Assemblage IUCN threat status was calculated using an unweighted mean. Additionally, the most vulnerable IUCN species threat status per assemblage was recorded (hereafter called maximum IUCN threat status).

4.3.6 Modeling species loss due to urbanization

To quantify differences in species richness, assemblage vulnerability, and IUCN threat status, we compared values between each urban polygon and its respective regional species pool. Differences in species richness, assemblage vulnerability, and mean IUCN threat status were then regressed onto regional species richness. Linear regressions and their respective r^2s and Ps were assessed using the glm() and summary() functions in base R [153]. This same approach was taken in order to assess whether assemblages with higher species richness had more vulnerable species (with either vulnerability scores or IUCN threat status).

To test whether vulnerable species (by both assemblage vulnerability or IUCN threat status) are being lost from the regional species pool at a rate higher than that expected by chance, paired regional and urban distributions were compared using the parametric paired t-test (first testing for normality using the Shapiro-Wilk test; all analyses used the functions t.test() and shapiro.test() included in base R; [153]). These tests take the difference at each city and compare them to a distribution centered around 0.

4.4 Results

4.4.1 Dataset description

The total number of checklists was 18,393, with a mean of 165.7 in each city-buffer combination. The Tegucigalpa-urban (Honduras) combination had the fewest checklists (10), and the 10-50 km buffer of San José (Costa Rica) had the most checklists (2,755). The 3,994 checklists for urban areas had a mean of 107.9 checklists/city, with a max. of 1,230 for Santiago (Chile). The 4,765 checklists for the 0-10 km buffers had a mean of 128.78 checklists/city-buffer, with a min. of 20 checklists for San Salvador (El Salvador), and a max. of 1,199 checklists for Oaxaca (Mexico). Finally, the 9,634 checklists for the 10-50 km buffers had a mean of 260.4 checklists/city-buffer, with a min. of 14 checklists for Bridgetown (Jamaica).

The "core" assemblages ultimately represent 37 cities with an urban assemblage and a regional species pool (Fig. 4.1). Urban assemblages contained a total of 827 species, with an average 22.35 species richness/urban polygon when rarefied to 10 checklists. Regional species pools contained a total of 1,729 species with an average of 46.73 species/regional species pool when based on the rarefied "core" assemblages. In most cities, buffer rarefied species richness increased both with regional species pool richness and with distance from the urban polygon (Fig. 4.2). This pattern was most consistent in city-buffer combinations where the regional species pool was highest. The linear models based on these relationships (buffer rarefied species richness $\sim$ regional species pool) were significant for all three buffers ($P < 0.05$, $r = 0.34$ for the urban polygon; $P < 5e\text{-}7$, $r = 0.75$ for the 0-10 km buffer; and $P < 5e\text{-}15$, $r = 0.92$ for the 10-50 km buffer).

The full dataset of 1,729 species had a mean IUCN threat level of 1.089 with a standard deviation of 0.41. Three species were "data deficient" (IUCN has not categorized them due to lack of data): the Mexican Woodnymph (*Thalurania ridgwayi*), the Stygian Owl (*Asio stygius*), and the Eared Poorwill (*Nyctiphrynus mcleodii*). These species were not found in

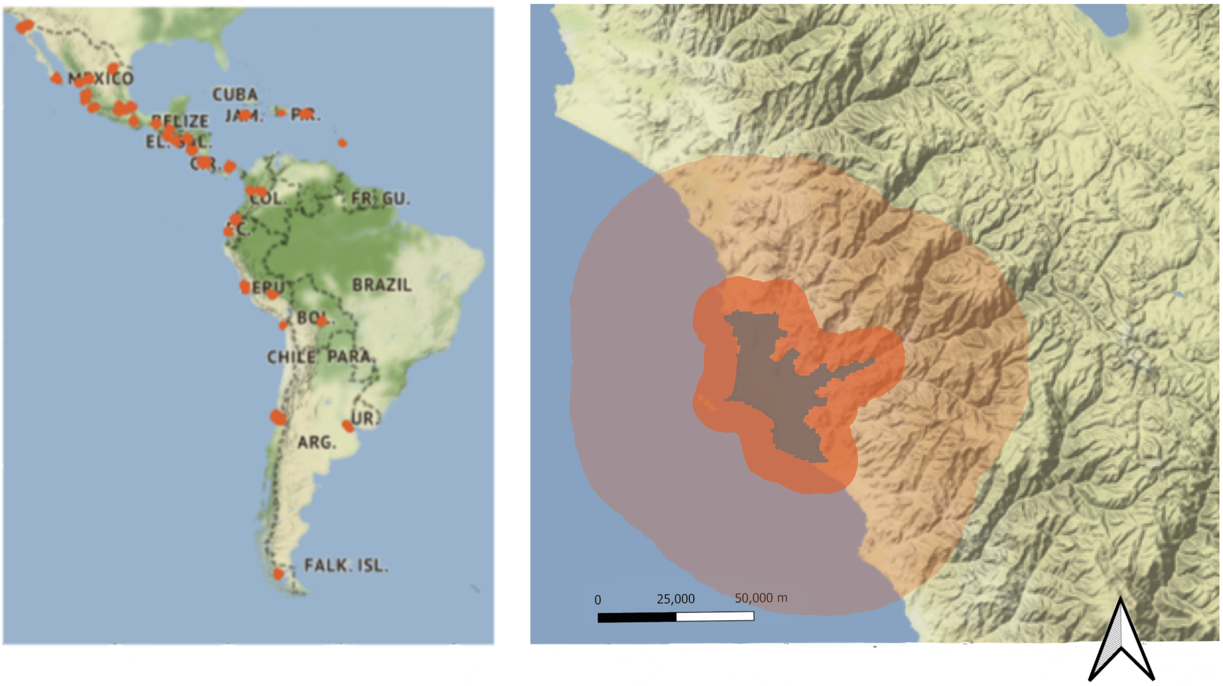

Figure 4.1: *Left*: The 37 city-buffer combinations that met the criteria of ten unique sampling days per buffer (urban, 0-10 km buffer, and 10-50 km buffer). *Right*: An example of these buffers (Lima, Perú). In gray, the urban polygon provided by the European Union Global Human Settlement geospatial database [64]. Dark orange is the 0-10 km buffer extending from the polygon, and in light orange is the 10-50 km buffer. The regional species pool for a city-buffer combination is all species found in all three buffers.

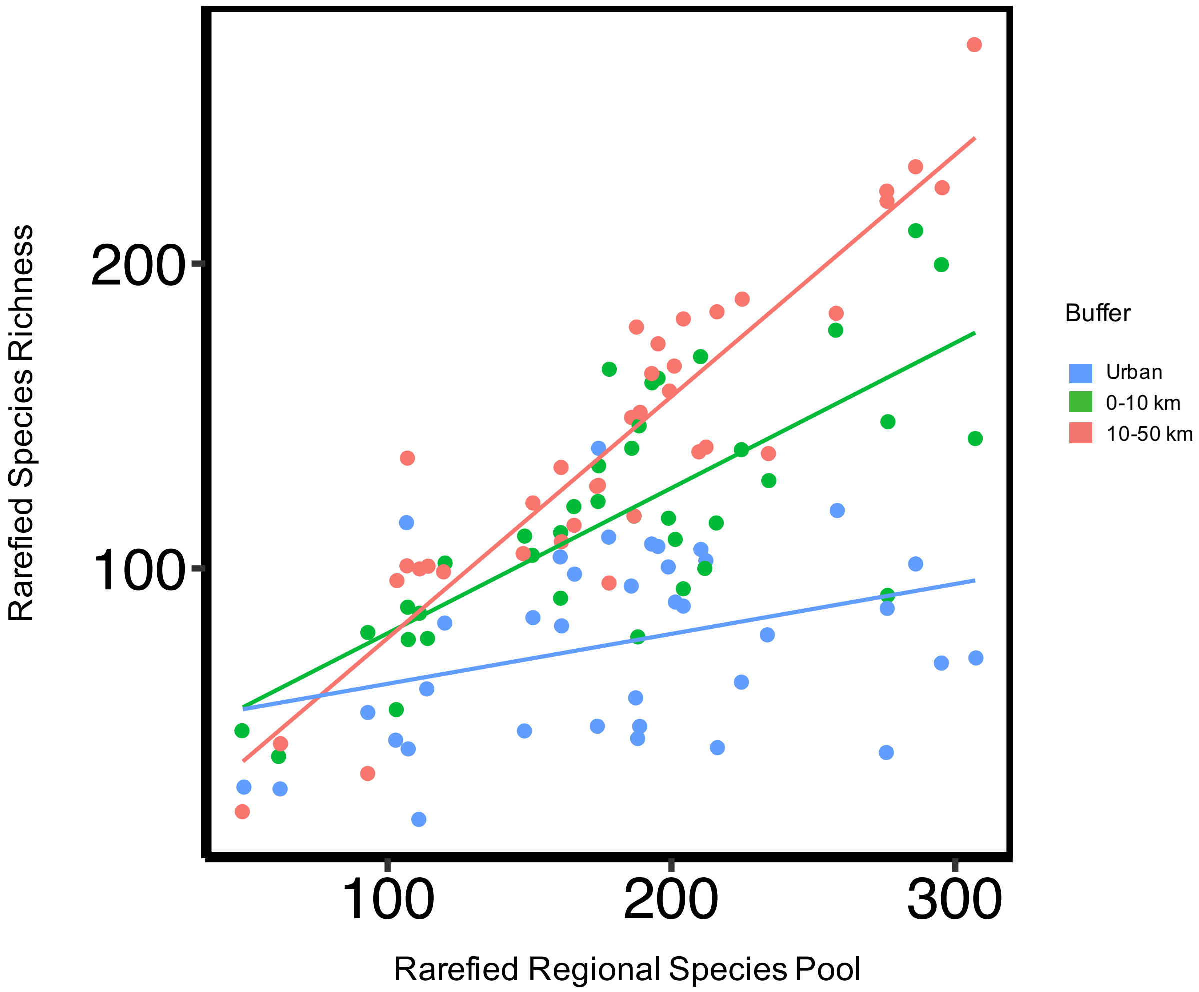

Figure 4.2: Rarefied species richness for urban "core" assemblage (blue), 0-10 km buffer "core" assemblage (green), and 10-50 km buffer "core" assemblage (red) against rarefied regional species pool richness (number of species that occur in any of the three "core" assemblages/city). Linear models ($y \sim x$) were significant for all three buffers ($P < 0.05$, $r = 0.34$ for the urban polygon; $P < 5e\text{-}7$, $r = 0.75$ for the 0-10 km buffer; and $P < 5e\text{-}15$, $r = 0.92$ for the 10-50 km buffer).

the urban assemblages. The species dataset also had a mean of 0 for vulnerability score (by definition, as all scores were standardized) with a standard deviation of 1. The most vulnerable species in the dataset, according to this index, was the Lesser Rhea (*Rhea pennata* with a species vulnerability score of 5.93). From the urban species list, the most vulnerable species was the Humboldt Penguin (*Spheniscus humboldti* with a species vulnerability score score of 2.13, found in Arica, on the Chilean border with Perú, and Viña del Mar, Chile). Of note, the buffers constructed on the coastal cities included eBird checklists submitted from boat trips. The least vulnerable species, according to this score, was the Brown-headed Cowbird (*Molothrus ater* with a species vulnerability score of -2.86).

4.4.2 Do speciose assemblages have more vulnerable species?

Assemblage vulnerability (mean of species vulnerability scores) and mean IUCN threat level were regressed against assemblage species richness, but no significant relationship was found (no P for either measurement was smaller than 0.05; Fig. 4.3, top row). The relationship when separated out into urban and regional groups was also not significant. The maximum species vulnerability score and maximum species IUCN threat level were also regressed against assemblage species richness (Fig. 4.3, bottom row). Only the maximum species IUCN threat level in the regional group showed statistical significance (Fig. 4.3, bottom right; maximum IUCN threat level $\sim$ rarefied species richness: $P < 0.05$, $r = 0.36$).

4.4.3 Do speciose assemblages proportionally lose more species?

The percentage of species richness lost in urban areas was significantly positively related to regional pool species richness (%species richness lost $\sim$ regional species pool richness: $P < 0.005$, $r = 0.45$, Figure 4.4 top left). The relationship between percentage of mean IUCN threat level lost in urban areas was slightly positive but also statistically significant (%mean IUCN threat level lost $\sim$ regional species pool richness: $P < 0.05$, $r = 0.34$, Figure 4.4, bottom left). Linear models were not able to explain the relationship between the

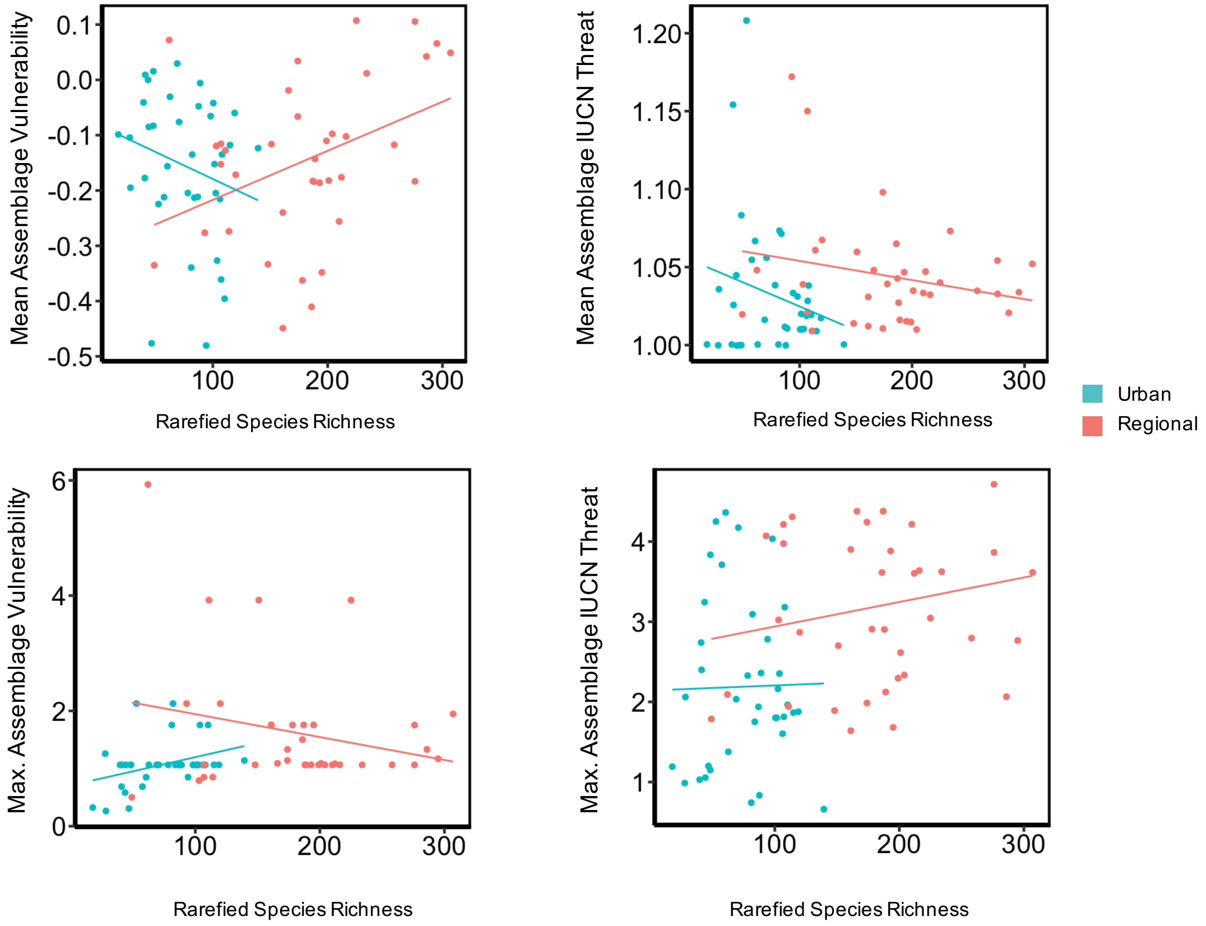

Figure 4.3: Top row of plots shows mean assemblage vulnerability by species richness (left) and mean IUCN threat level by species richness (right). Bottom row shows maximum species vulnerability score by assemblage species richness (left) and maximum species IUCN threat level by assemblage species richness (right). Data points for regional species pools are in red and data points for urban polygon assemblages are in blue.

percentage of assemblage vulnerability lost even when the extreme outlier (loss of 1818% of vulnerability) was excluded (Figure 4.4, top right for inclusion of data point, bottom right without data point). This extreme data point represents Bogota (Colombia), which went from a regional assemblage vulnerability of 0.119 to an urban assemblage vulnerability of -0.2045, driven by a loss of 109 species with relatively high vulnerability scores (0 and 0.50).

4.4.4 Do these assemblages do so because they lose vulnerable species first?

Paired urban-regional differences in assemblage vulnerability and mean IUCN threat level were normally distributed (Shapiro-Wilk normality test, P = 0.56 and P = 0.88, respectively), and thus appropriate for the parametric paired t-test. The paired t-test for the assemblage vulnerability differences do not suggest a true difference not equal to 0 (mean difference = 0.01, P = 0.52, df = 36), while it does for mean IUCN threat level (mean = 0.01, P <0.0005, df = 36), supporting the hypothesis that regional species pools have a true higher mean IUCN threat level than urban assemblages do.

4.5 Discussion

Assemblages with higher species richness do not seem to have more vulnerable species (by vulnerability score or by IUCN threat status level; Figure 4.3, top row). Assemblages with higher species richness can, however, support individual species with a higher IUCN threat status than assemblages with lower species richness (Figure 4.4, bottom right). We show that urbanization may affect biodiverse places in proportionally more intense ways, despite evidence that biodiversity provides compositional resilience and resistance to assemblages in the face of short-term pressures and disturbances (Figure 4.4, top left; [178]). Finally, this seems to be driven by significant losses in species with a higher IUCN threat status, and not by significant losses in vulnerable species according to the metric used. Instead,

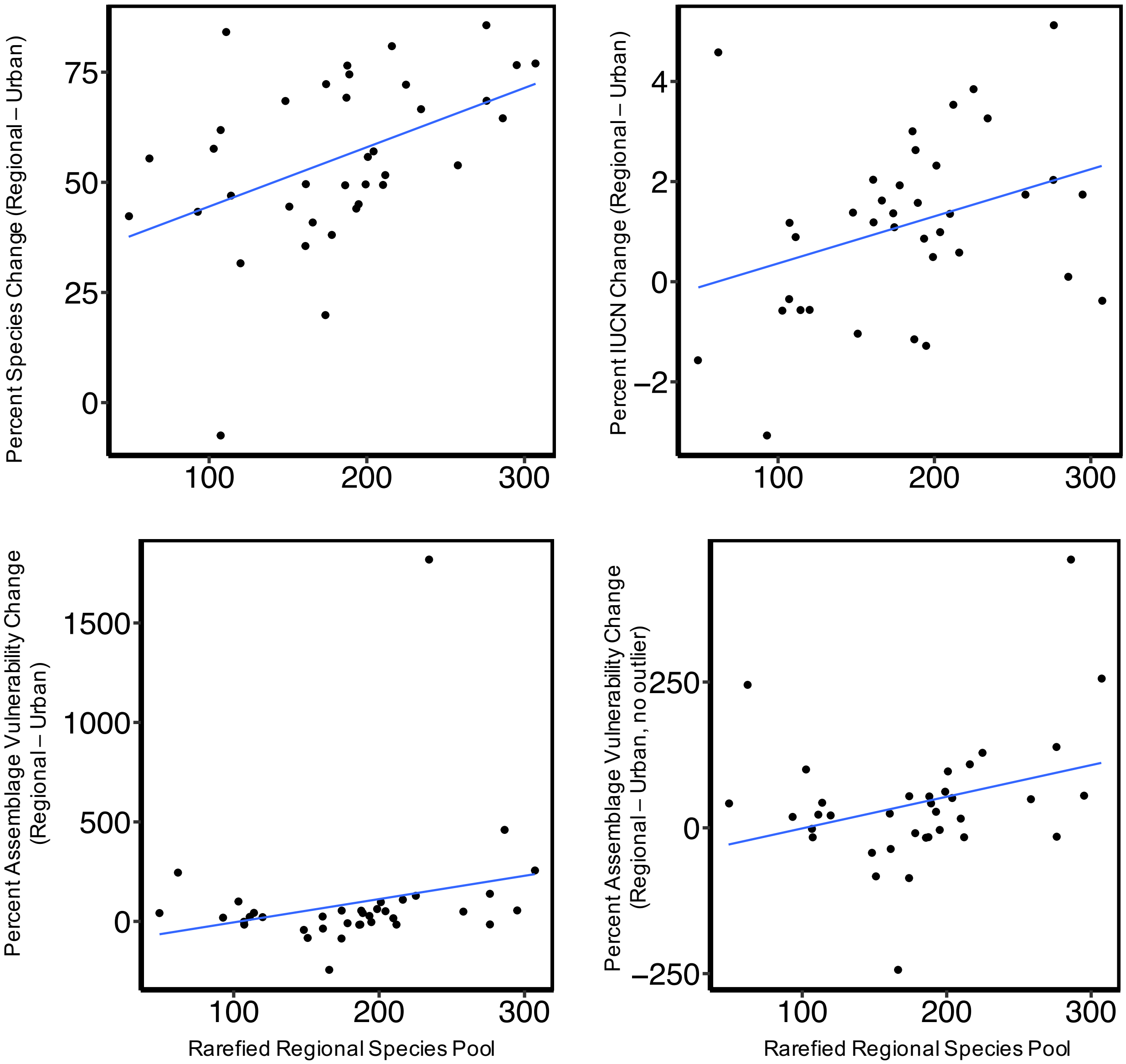

Figure 4.4: Linear relationships between percent variable loss (regional species pool – urban assemblage) and regional pool species richness (blue line) for species richness (top left), mean IUCN threat level (top right), assemblage vulnerability (bottom left), and assemblage vulnerability excluding Bogota (bottom right; see text). Peripheral points on bottom right plot include: Punta Arenas (245% change), Guatemala City (-244% change), Panama City (460% change), and San Jose (255% change).

the changes in distributions of assemblage vulnerability of regional species pool and their respective urban assemblage seem to not change the overall distribution, suggesting that lack of occurrence in urban areas for a particular species may reflect an upper limit of species richness for urban areas.

In order to assess if there is an upper limit of species richness for urban areas, it would be fruitful to understand if this upper limit changes with urban variables (such as, density of humans, percent greyspace, urbanized area, time since initial urbanization, and percent greenspace) or with environmental factors (latitude, ecoregion/climatic region, biogeographic history, elevation, continental or island). By exploring this question, we could assess if the upper limit in this dataset is an urban rule or if it is the result of a particular ecosystem-variable interaction. We could also assess whether the same pattern found with the vulnerability scores is occurring in other metrics (as in, do we see representatives of each morphological type/trope, foraging guild, or phylogenetic order in the urban area or does the urban area filter out some types/tropes/guilds/orders selectively?). Furthermore, this would inform relationships between biodiversity and ecological functioning in urban areas—answering questions such as: Are functions (movement of nutrients/biomass/energy through different trophic levels) happening via non-human species or are humans replacing particular organisms' roles in those interactions?; Are particular species more likely to represent a functional type and what about them (for example, ability to disperse into an urban area) makes them more likely to do so? If this is happening, it would support the theory of biotic homogenization, a process in which species with particular urban attributes end up comprising the majority of all urban biotic communities [123]. Thus, there may exist a saturating relationship between diversity and function, where functions are first represented by a homogenized community and if other species enter, they fulfill similar functions (relationships as described in [81, 177].

These sorts of relationships are already being assessed in other datasets. For example, in a comparative study of 41 European cities, the proportion of regional avian species represented by urban assemblages went up as latitude went up—if we take latitude to be a proxy for species richness and/or biodiversity, we can assume that similar patterns are happening in Europe as what we demonstrate in Latin America ([59]; Figure 4.2, top left). Using similar trait databases, Sol et al. [168] showed that urbanized environments have substantially different functional composition and 20% less functional diversity on average than surrounding natural habitats. While this study may suggest that biotic homogenization is happening, it did not assess whether or not species pools with higher species richness are differentially affected, and thus cannot answer whether or not increased biodiversity makes an assemblage more or less protected against dramatic land-use change [168]. Some studies have been able to assess which species can persist in urban environments, and their traits, but not have made the link between these traits and ecological function and functional diversity (i.e. [45]), while others make the link between urban form and biodiversity, highlighting the importance of both water environments and greenspace (i.e. [86, 18], without bringing in ecoregion variables. Making links between all these facets and understanding humans' role in ecological functions would be helpful in designing global and regional urban planning measures for biodiversity. For example, understanding that avian insectivores and open habitat species are the first to be lost in some cities (i.e. [166]) may incentivize the planting of wetland grass species along coasts (f. ex. reeds to attract swallows that would reduce mosquito populations without the need of insecticide and provide resilience against hurricanes, [159]).

Finally, an assessment of the strength of using eBird data and IUCN threat status is important. In the present study, eBird data was treated appropriately in order to strengthen the validity of the results. For example, we used data from a period of ten years in order to expand the range of cities that we could include, but also used conservative criteria to assure that the final species lists did not include any misidentified or vagrant bird species (ten unique sampling days, c.f. [191], and dropping singletons). An important caveat to the study is to understand that we are comparing urban assemblages to regional species pools, and not delving into what the ex-urban communities look like. Investigating the differences between these groups of birds may also hold insights into the dynamics between the habitat conditions. Additionally, the presented results may be validated by re-running analyses using regional species pools attained from BirdLife range maps, and by comparing those regional species pools to the ones in this study attained from eBird. Finally, IUCN threat statuses are based on five criteria measuring different aspects of population size, geographic range, and probability of extinction, where critically endangered (here, score of 5) means over 50% chance of extinction in 10 years or 3 generations, and vulnerable (score of 3) means over 10% chance of extinction in 100 years [170]. While these have been useful standards for conservation prioritization, there has been debate about the process by which these standards are assessed in difficulty of changing category, validity of data provided, and relevancy to pressing threats such as climate change (i.e. [97, 154]). Understanding whether the same patterns are seen according to other criteria regarding extinction probability would be useful in assessing the threat of urbanization on biodiverse systems.

If the results to the aforementioned questions show that urban areas retain functioning ecosystems and functional diversity, albeit lower species richness, where does that leave biodiversity priorities in conservation? Our results suggest that biodiversity still supports species with high extinction risk as defined by IUCN– and that dramatic land-use change, such as urbanization, could wipe them out. According to a recent study [185], vulnerable (defined there differently) species are more likely to exist in diverse assemblages, while assemblages with lower diversity have a higher mean IUCN threat level. This suggests that “vulnerable” species accumulated in diverse assemblages may be less “threatened” because they are being protected by biodiverse systems (see also [186]), while IUCN threat level reflects anthropogenic processes actively putting pressure upon particular species. If this is the case, conservation priorities would be well placed around biodiverse systems to keep “vulnerable” species from becoming “threatened” by IUCN standards.

4.6 Conclusion

We show that regional species pools with high species richness proportionally lose more species in their urban components than regional species pools with lower species richness, contradicting our expectations that high biodiversity may help protect assemblages from anthropogenic change, given the biodiversity and ecosystem functioning relationships established in experimental and short-term observational studies. While this may seem like an unexpected result, there are reasons to predict this result, as some authors show a diversity-function saturating relationship under certain conditions (for example, [81, 177]). Our results may add another condition under which the relationship saturates, without preferentially filtering out vulnerable species. Despite these results, we also show that regional species pools with higher species richness are more likely to harbor species with a higher IUCN threat status, suggesting that in order to protect these species, focusing conservation priorities on protecting biodiverse systems continues to be a viable strategy.

4.7 Acknowledgments

A deep thank you to Nicholas Knoblauch, Jacob Cooper, Katie Silliman, and Claudio Gómez-Gonzáles for computing help. Sebastian Heilpern and Brian Weeks have both contributed significantly to this work, where S. H. was part of the original conception of this project, and both S. H. and B. W. participated in weekly discussions regarding this project and gave substantial comments to the chapter. Joseph Tobias contributed over 90% of the morphological data that will be used in the published version of this paper, while Ilana Malekan, Melissa Molina, Suzie Oppenheimer, and Alicia Srinivas all helped measure the remaining species' representative specimens at the Field Museum of Natural History and at the California Academy of Sciences; an additional thanks to the American Museum of Natural History that allowed me to visit and measure the handful of species not covered above. A thank you to the members of the Bates/Hackett and Price labs for discussion, and

the staff at all these natural history institutions that steward over the specimen collections.

CHAPTER 5

CONCLUSIONS AND FURTHER RESEARCH

This dissertation points to an important conclusion: to understand urban ecological systems and have that understanding influence decisions and actions within that city, local knowledge and involvement is fundamental. The first study presented showed that visual methods accompanied by local knowledge can provide lower cost, more accurate environmental classifications than turn-key algorithms provided by popular software, obviating the necessity for the expensive software for urban ecology and planning research. The second study demonstrated that local urban populations are often already connected to nature, at least in curiosity, and as environmental researchers our questions should not be "Are they connected to nature?" but "*How* are they connected to nature?." The third study showed that urban areas may support assemblages that functionally look similar to their regional species pool but hold much fewer species (potentially up to a limit) and do not support highly threatened species (as assessed by IUCN). What that means as far as recommendations to support more species or those threatened within the city may depend on the city itself: what it looks like, what the surroundings are, who lives in it, what species are prioritized, and which ecological functions are being performed by humans.

If the conclusion is taken seriously, that urban ecology needs to be participatory, each study also signifies different research trajectories. The first study opens up questions about technology and the expectations of technology in knowledge production and policy creation. When governments see authoritative and "legitimate" knowledge as tied to academic institutions, and academic institutions measure worth by journal articles, and journal articles value the most sophisticated, innovative methods (a point driven home to me by the journal reviewer comments I received for this chapter), it by definition excludes those without access to those technologies or academic institutions from producing authoritative and "legitimate" knowledge to influence policy creation and decision-making. Additionally, as conservation technology continues to become more common-place and therefore expected in the production of this knowledge and implementation of policies, it places communities at the mercy of technical support from non-governmental agencies and governmental agencies that benefit from international cooperation and funding priorities. This study shows that what would have been considered sophisticated ten years ago is not as good as the low-technology option, and that what is sophisticated now is simply inaccessible for community members. Understanding how technology and educational institutions shape this power imbalance, particularly in the time of a pandemic where much of education is done virtually (and the accompanying proliferation of crowd-funding to support those that do not have the technology to access that education) is paramount to understanding which participatory research actually closes this power gap, and which perpetuates it. A research question that would help elucidate this is identifying how technology and internet access are implemented in the global South, who decides where this happens, who implements it, and which policies are accepted using low-technology and local research.

The second study questions how we think about human-nature connectedness. As I expanded upon in this chapter, what we have often considered to be the ways in which we show connectedness to nature from an academic perspective (visiting parks, camping, donating money to environmental groups, and voting for politicians based on environmental issues) is narrow in comparison to the history and perspectives of environmental culture. Contrary to the idea that urban residents are losing their connection to nature, our results suggest that "knowledge" about the birds in one's neighborhood has more to do with the socioecological history of a city than with its being a city, and that "curiosity" is present no matter what city the respondents reside in. A further question to this study is what to do with this information—Can this information become a baseline to implement environmental education and citizen science initiatives? Additionally, moving the human-nature research from "Are people connected to nature?" to "How are people connected to nature?" opens up a field of discovery and dialogue on the different ways in which people can value nature and can inspire more hopeful conservation stories than what we find in a climate change crisis and sixth mass extinction. Taking the time to understand where one works and realizing that the natural history of a place is imbued with the cultural history of a place is a pathway for a broader understanding of the human-nature relationship.

The third study has multiple directions in which it can be followed, from fundamental ecological questions both about bird communities but also how we think about bird communities, to research that can be scaled down to ask about individual cities, to implications about the ways to utilize and engage urban residents in citizen science initiatives. There are some analyses pending for a published version, in particular around the definition of "vulnerability." From preliminary data, it seemed that while morphological tropes are represented in urban assemblages, the regional species pool simply had multiple representatives for those morphological tropes. One fruitful trajectory would be understanding what morphological tropes even are: What are the criteria we set for them and what do they look like under different criteria? How flexible are they when taking into account variable species behavior? Another would be to understand what is going on in each individual city: Do these species lists look similar to each other in composition and in functional tropes? Can ideas about morphological variation be scaled down to an intra-city analysis? Anecdotally, it seemed that the cities in the coastal deserts were able to support more threatened species (i.e. Humboldt Penguin), raising the question of what role does the ocean play in creating urban bird communities? What are the criteria for being part of an urban community? Finally, can these species lists be used to incentivize folks into participating in birdwatching activities? Do people find it inspiring to link their city to others? Do the same incentives for bird watchers in the global North work in the global South?

While only one of the three studies presented addressed the original proposed question, how does nature use urban space?, the other two delved into how we think about both urban space and nature. The ways in which we think about ecology and evolution ultimately shape our questions, our methodologies, and our understanding about ecology and evolution. Without questioning these, we may miss crucial patterns in ecology and evolution. In a time of climate change crisis and sixth mass extinction, solutions seem less a question of scientific consultation, but one of political will—and in a world where political power is concentrated in corporations and pet governments, the question of returning political power and autonomy to local peoples, in and outside of cities, seems like the clearest path to a restorative nature.

APPENDIX A

SURVEY MATERIALS (CHAPTER 3)

A.1 Consent Language

Por favor considere participar en esta encuesta voluntaria. La encuesta solo debe tomar 10 minutos para completar y los datos no estarán vinculados a su identidad. Como investigadores, estamos tratando de entender cómo la gente de esta ciudad interactúa con la naturaleza y cuánto conoce de las aves en su alrededor. Estos datos se usarán para la tesis de doctorado de la Bióloga Natalia Piland. Puede contactarla con cualquier pregunta al correo: npilanduchicago.edu

A.2 Survey

Nota para el/la encuestador/a: Esta encuesta se ha diseñado para entender algunos factores que podrían afectar cómo un/a ciudadan se relaciona con la naturaleza en su vecindario/barrio. Entre estos factores se encuentran edad, nivel de educación, duración en el barrio, origen, tiempo que se realiza y tipo de actividades realizados afuera. La relación que se percibe en esta encuesta con la naturaleza es conocimiento de aves y motivación en conocer más sobre las aves. Esto se correlacionará con información obtenida sobre cada localidad en cuanto a diversidad de aves observado y algunos factores ambientales cómo porcentaje de áreas verdes que se medirán a través del monitoreo remoto.

Localidad:

Fecha:

Encuestador/a:

Encuestad (Si se siente comod):

¿Cuál es su fecha de nacimiento?

¿Cómo se identifica en cuanto a género?

¿Qué nivel de estudios tiene?

Primaria Completa / Primaria Incompleta

Secundaria Completa / Secundaria Incompleta

Estudios técnicos completos / incompletos

Universitario completo/ incompleto

Posgrado completo/incompleto

¿A qué se dedica? ¿En qué trabaja?

¿Desde que año usted vive en este barrio?

¿Dónde vivía antés de mudarse a este barrio?

¿Qué tipo de actividades realiza afuera de su casa en el barrio?

Sentarse a tomar sol/respirar aire fresco

Caminar por el barrio/en un parque cercano

Jugar deportes

Otro:

¿Cuántas horas semanales pasa realizando esas actividades?

Poco (1 hora/semana – 4 horas/semana)

Regular (4 – 10 horas/semana)

Mucho (10+ horas/semana)

¿Tiene mascotas?

¿Cuáles y cuántas?

¿Los deja salir afuera?

¿Tiene un jardín?

¿Qué tipos de plantas tiene en el jardín?

¿Ud. ha observado aves en el barrio?

¿Aproximadamente cuántos diferentes tipos de aves estima que ha visto aquí?

¿Puede nombrar algunas de las aves que ha visto?

En su opinión, estima que la diversidad de aves que hay en este vecindario es:

Sólo hay pocos tipos de aves

Normal

Muchos diferentes tipos de aves

No sabe

¿Conoce el nombre de las siguientes aves? (Enseñar lamina de aves)

1

2

3

4

5

6

7

8

9

10

¿Le gustaría más información de las aves que se encuentran aquí? SÍ / NO

¿Qué tipo de información le gustaría obtener?

APPENDIX B

DESCRIPTIVE STATISTICS (CHAPTER 3)

Table B.1: Table summarizing all independent variables from the survey by city, and then in total. For categorical variables raw numbers are presented with their proportion of the group in parenthesis. For quantitative variables, distribution parameters minimum, mean, standard deviation, median, and maximum are presented for each group. 963 individuals were surveyed in total.

Variable	**Huacho**	**Lima**	**Iquitos**	**Nauta**	**Total**
Gender Presentation					
Feminine	96 (53.3%)	175 (52.7%)	193 (55.1%)	44 (43.6%)	508 (52.8%)
Masculine	79 (43.9%)	152 (45.8%)	156 (44.6%)	57 (56.4%)	444 (46.1%)
No Response	5 (2.8%)	5 (1.5%)	1 (0.3%)	0 (0.0%)	11 (1.15%)
Total	180	332	350	101	963
Age					
Mean (sd)	41.3 (19.3)	43.5 (19.5)	40.8 (18.5)	41.4 (16.1)	41.9 (18.8)
Minimum	7	7	4	12	4
Median	38	42	39	42	40
Maximum	86	92	86	78	92
No Response	3	9	1	0	13
Education					
None	0 (0%)	0 (0%)	4 (1.1%)	1 (1.0%)	5 (0.5%)
Primary - Incomplete	6 (3.3%)	10 (3.0%)	24 (6.9%)	18 (17.8%)	58 (6.0%)
Primary - Complete	13 (7.2%)	21 (6.3%)	20 (5.7%)	10 (9.9%)	64 (6.6%)
Secondary - Incomplete	22 (12.2%)	27 (8.1%)	63 (18%)	19 (18.8%)	131 (13.6%)
Secondary - Complete	65 (36.1%)	0 (0%)	98 (28%)	21 (20.8%)	184 (19.1%)
Technical Studies - Incomplete	2 (1.1%)	14 (4.2%)	13 (3.7%)	1 (1.0%)	30 (3.1%)
Technical Studies - Complete	17 (9.4%)	46 (13.9%)	37 (10.6%)	10 (9.9%)	110 (11.4%)
University - Incomplete	15 (8.3%)	31 (9.3%)	38 (10.9%)	3 (3.4%)	87 (9.0%)
University - Complete	33 (18.3%)	72 (21.7%)	53 (15.1%)	17 (16.8%)	275 (28.6%)
Postgraduate	2 (1.1%)	5 (1.5%)	0 (0.0%)	1 (1.0%)	5 (0.5%)
No Response	5 (2.8%)	6 (1.8%)	0 (0.0%)	0 (0.0%)	11 (1.15%)
Total	180	332	350	101	963

Variable	**Huacho**	**Lima**	**Iquitos**	**Nauta**	**Total**
Work					
Accommodation and Food Services	5 (2.8%)	7 (2.1%)	5 (1.4%)	0 (0.0%)	17 (1.8%)
Administrative and Support Services	4 (2.2%)	22 (6.6%)	7 (2.0%)	0 (0.0%)	33 (3.4%)
Agriculture, Forestry, Fishing, and Hunting	7 (3.9%)	0 (0.0%)	3 (0.9%)	15 (14.9%)	25 (2.6%)
Arts, Entertainment, and Recreation	3 (1.7%)	7 (2.1%)	5 (1.4%)	1 (1.0%)	16 (1.7%)
Construction	5 (2.8%)	4 (1.2%)	9 (2.6%)	6 (5.9%)	24 (2.5%)
Educational Services	4 (2.2%)	9 (2.7%)	21 (6.0%)	16 15.8%)	50 (5.2%)
Finance and Insurance	1 (0.6%)	8 (2.4%)	0 (0.0%)	0 (0.0%)	9 (0.9%)
Freelance	12 (6.7%)	11 (3.3%)	37 (10.6%)	7 (6.9%)	67 (7.0%)
Health Care and Social Assistance	5 (2.8%)	10 (3.0%)	4 (1.1%)	1 (1.0%)	20 (2.1%)
Information	1 (0.6%)	2 (0.6%)	0 (0.0%)	0 (0.0%)	3 (0.3%)
Management of Companies and Enterprises	7 (3.9%)	9 (2.7%)	0 (0.0%)	0 (0.0%)	16 (1.7%)
Manufacturing	2 (1.1%)	4 (1.2%)	4 (1.1%)	0 (0.0%)	10 (1.0%)
Mining, Quarrying, Oil, and Gas Extraction	0 (0.0%)	1 (0.3%)	0 (0.0%)	0 (0.0%)	1 (0.1%)
Other Services	45 (25.0%)	63 (19.0%)	79 (22.6%)	28 (27.7%)	215 (22.3%)
Professional, Scientific, and Technical Services	2 (1.1%)	13 (3.9%)	12 (3.4%)	2 (2.0%)	29 (3.0%)
Public Administration	3 (1.7%)	10 (3.0%)	9 (2.6%)	0 (0.0%)	22 (2.3%)
Retail Trade	17 (9.4%)	62 (17.7%)	34 (10.2%)	10 (9.9%)	123 (12.8%)
Retired	14 (7.8%)	30 (9.0%)	10 (2.9%)	0 (0.0%)	54 (5.6%)
Student	33 (18.3%)	51 (15.4%)	61 (17.4%)	11 (10.9%)	156 (16.2%)
Transportation and Warehousing	3 (1.7%)	7 (2.1%)	6 (1.7%)	2 (2.0%)	18 (1.9%)
Unemployed	0 (0.0%)	7 (2.1%)	16 (4.6%)	2 (2.0%)	25 (2.6%)
Utilities	1 (0.6%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (0.1%)
Wholesale Trade	0 (0.0%)	1 (0.3%)	0 (0.0%)	0 (0.0%)	1 (0.1%)
No Response	6 (3.3%)	22 (6.6%)	0 (0.0%)	0 (0.0%)	28 (2.9%)
Total	180 (100%)	350 (100%)	332 (100%)	101 (100%	963 (100%)
Years in Current Residence					
Mean (sd)	19.8 (18.7)	19.8 (17.7)	18 (15.2)	15.1 (16)	18.7 (16.9)
Minimum	0	0	0	0	0
Median	15	16	15	10	15
Maximum	81	84	75	73	84
No Response	1	1	1	0	3
Last Move					
Never moved	48 (26.7%)	75 (22.6%)	57 (16.3%)	13 (12.9%)	193 (20%)
Same Neighborhood	0 (0.0%)	35 (10.5%)	50 (14.3%)	2 (2%)	42 (4.4%)
Same City	63 (35%)	123 (37.0%)	185 (52.9%)	27 (26.7%)	398 (41.3%)
Urban to Urban	29 (16.1%)	36 (10.8%)	44 (12.6%)	21 (20.8%)	130 (13.5%)
Rural to Urban	27 (15%)	19 (5.7%)	51 (14.6%)	36 (35.6%)	133 (13.8%)
International	0 (0.0%)	8 (2.4%)	0 (0.0%)	0 (0.0%)	8 (00.8%)
No Response	13 (7.2%)	36 (10.8%)	8 (2.3%)	2 (2%)	59 (6.1%)
Total	180 (100%)	350 (100%)	332 (100%)	101 (100%	963 (100%)
Activities Outside					
Exercise	32 (17.8%)	61 (18.4%)	100 (28.6%)	35 (34.7%)	228 (23.7%)
Extractive	5 (2.8%)	11 (3.3%)	6 (1.7%)	8 (7.9%)	30 (3.1%)
Recreation	102 (56.7%)	234 (70.5%)	199 (56.9%)	42 (41.6%)	577 (59.9%)
Work	14 (7.8%)	11 (3.3%)	26 (7.4%)	15 (14.9%)	66 (6.9%)
Other	0 (0.0%)	0 (0.0%)	1 (0.3%)	0 (0.0%)	1 (0.1%)
None	29 (16.1%)	36 (10.8%)	35 (10.0%)	8 (7.9%)	108 (11.2%)
No Response	9 (5.0%)	10 (3.0%)	0 (0.0%)	0 (0.0%)	19 (2%)
Total	180 (100%)	350 (100%)	332 (100%)	101 (100%	963 (100%)
Hours Outside					
None	29 (16.1%)	36 (10.8%)	35 (10.0%)	8 (7.9%)	108 (11.2%)
Few (1-4)	72 (40%)	121 (36.4%)	163 (46.6%)	39 (38.6%)	395 (41%)
Regular (4-10)	34 (18.9%)	105 (31.6%)	104 (29.7%)	36 (35.6%)	279 (29%)
Many (10+)	40 (22.2%)	70 (21.1%)	46 (13.1%)	18 (17.8%)	174 (18.1%)
No Response	5 (2.8%)	0 (0.0%)	2 (0.6%)	0 (0.0%)	7 (0.7%)
Total	180 (100%)	350 (100%)	332 (100%)	101 (100%	963 (100%)

Table B.2: Table summarizing all response variables from the survey by city, and then in total. For categorical variables raw numbers are presented with their proportion of the group in parenthesis. For quantitative variables, distribution parameters minimum, mean, standard deviation, median, and maximum are presented for each group. 963 individuals were surveyed in total.

Variable	**Huacho**	**Lima**	**Iquitos**	**Nauta**	**Total**
Engagement					
Has Pets	88 (49.4%)	168 (50.8%)	208 (59.4%)	48 (47.5%)	512 (53.3%)
No Pets	90 (50.6%)	163 (49.2%)	142 (40.6%)	53 (52.5%)	448 (46.7%)
Has Garden	47 (26.4%)	97 (29.5%)	202 (57.7%)	65 (64.4%)	411 (42.9%)
No Garden	131 (73.6%)	232 (70.5%)	148 (42.3%)	36 (35.6%)	547 (57.1%)
#Garden Species					
Mean (sd)	0.5 (1)	0.7 (1.3)	1.6 (1.6)	2.8 (2.1)	1.1 (1.6)
minimum	0	0	0	0	0
median	0	0	1	3	0
maximum	5	8	7	10	10
No response	2 (1.11%)	10 (3.01%)	148 (42.3%)	36 (35.6%)	196 (20.35%)
Perception					
Sees birds	173 (96.7%)	318 (96.1%)	332 (94.9%)	91 (90.1%)	914 (95.1%)
Does not see birds	6 (3.4%)	13 (3.9%)	18 (5.1%)	10 (9.9%)	47 (4.9%)
Not sure	10 (5.8%)	12 (3.7%)	5 (1.4%)	5 (5.0%)	32 (3.4%)
Low biodiversity	107 (61.5%)	173 (53.2%)	257 (73.6%)	71 (70.3%)	608 (64.1%)
Normal biodiversity	40 (23.0%)	101 (31.1%)	72 (20.6%)	18 (17.8%)	231 (24.3%)
High biodiversity	17 (9.8%)	39 (12.0%)	15 (4.3%)	7 (6.9%)	78 (8.2%)
No response	6 (3.3%)	7 (2.1%)	1 (0.29%)	0 (0%)	14 (1.45%)
#Estimated Bird Species					
Mean (sd)	4.3 (8.5)	4.6 (6.7)	4.4 (3.5)	4.6 (5.5)	4.5 (6)
minimum	0	0	0	0	0
median	2.5	3	4	4	3.5
maximum	100	100	25	50	100
No response	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Knowledge					
#Responses					
Mean (sd)	3.6 (1.9)	4.2 (1.9)	5.4 (1.9)	7.9 (2.2)	4.9 (2.3)
minimum	0	0	0	0	0
median	4	4	5	9	5
maximum	9	10	10	10	10
No response	1 (0.6%)	1 (0.3%)	0 (0%)	0 (0%)	2 (2.1%)
#Correct (Lists)					
Mean (sd)	3 (2)	3 (2)	5 (2)	7 (2)	4 (2)
minimum	0	0	0	0	0
median	2	3	5	7	4
maximum	7	8	9	9	9
No response	11 (6.1%)	1 (0.3%)	5 (1.4%)	0 (0%)	17 (1.77%)
#Correct (Popular)					
Mean (sd)	2 (1)	3 (2)	5 (2)	6 (2)	3 (2)
minimum	0	0	0	0	0
median	2	3	5	7	3
maximum	7	7	9	9	10
No response	11 (6.1%)	0 (0%)	5 (1.4%)	0 (0%)	15 (1.56%)
More Info					
More Info - Yes	135 (75%)	247 (74.6%)	287 (82%)	92 (91.1%)	761 (79.1%)
More Info - No	45 (25%)	84 (25.4%)	63 (18%)	9 (8.9%)	201 (20.9%)
#Categories					
Mean (sd)	1.1 (0.9)	1.2 (1)	1.2 (1)	1.4 (1.1)	1.2 (1)
minimum	0	0	0	0	0
median	1	1	1	1	1
maximum	5	6	4	5	6
No response	0 (0%)	1 (0.3%)	0 (0%)	0 (0%)	1 (0.1%)
BirdIndirect	15 (8.3%)	26 (7.8%)	59 (16.9%)	13 (12.9%)	113 (11.7%)
BirdIntrinsic	86 (47.8%)	184 (55.4%)	222 (63.4%)	66 (65.3%)	558 (57.9%)
HumanAesthetic	1 (0.6%)	3 (0.9%)	3 (0.9%)	0 (0%)	7 (0.7%)
HumanDirect	30 (16.7%)	53 (16%)	19 (5.4%)	10 (9.9%)	112 (11.6%)
HumanIndirect	5 (2.8%)	6 (1.8%)	3 (0.9%)	8 (7.9%)	22 (2.3%)
HumanIntrinsic	15 (8.3%)	24 (7.2%)	20 (5.7%)	11 (10.9%)	70 (7.3%)
HumanRecreational	4 (2.2%)	6 (1.8%)	3 (0.9%)	2 (2%)	15 (1.6%)
No Response	47 (26.1%)	86 (26%)	84 (24%)	16 (15.8%)	233 (24.2%)
Responses/Individuals	207/180	388/332	413/350	126/101	1130/963

Table B.3: Table summarizing all environmental variables from the survey by city, and then in total. Distribution parameters minimum, mean, standard deviation, median, and maximum are presented for each group. There were 97 sites in total.

Variable	**Huacho**	**Lima**	**Iquitos**	**Nauta**	**Total**
Land Cover Metrics					
Local Tree Cover					
Mean (sd)	7% (6%)	14% (15%)	13% (9%)	28% (10%)	10% (10%)
minimum	0%	1%	5%	10%	0%
median	5%	10%	10%	30%	10%
maximum	20%	70%	40%	40%	70%
Number of sites	18	34	35	10	97
Local Grass Cover					
Mean (sd)	5% (5%)	10% (7%)	14% (8%)	20% (8%)	10% (10%)
minimum	0%	0%	0%	10%	0%
median	4%	10%	15%	20%	10%
maximum	15%	20%	30%	35%	30%
Number of sites	18	34	35	10	97
Local Building Cover					
Mean (sd)	59% (16%)	59% (20%)	57% (17%)	29% (15%)	60% (20%)
minimum	30%	0%	20%	10%	0%
median	58%	62%	60%	25%	60%
maximum	85%	85%	85%	60%	80%
Number of sites	18	34	35	10	97
Neighborhood Tree Cover					
Mean (sd)	4% (3%)	8% (4%)	11% (6%)	24% (8%)	10% (10%)
minimum	0%	2%	1%	10%	0%
median	4%	5%	10%	25%	10%
maximum	10%	20%	25%	35%	30%
Number of sites	18	34	35	10	97
Neighborhood Grass Cover					
Mean (sd)	8% (6%	7% (3%)	16% (10%)	21% (8%)	10% (10%)
minimum	0%	0%	3%	10%	0%
median	6%	10%	15%	20%	10%
maximum	20%	10%	40%	35%	40%
Number of sites	18	34	35	10	97
Neighborhood Building Cover					
Mean (sd)	54% (17%)	66% (9%)	53% (16%)	25% (9%)	60% (20%)
minimum	30%	40%	15%	10%	10%
median	50%	66%	60%	28%	60%
maximum	80%	80%	80%	40%	80%
Number of sites	18	34	35	10	97
Nearest Landmark Metrics					
Distance to Park (m)					
Mean (sd)	121.21 (185)	77.89 (133)	109.22 (113)	52.36 (55)	94.6 (132.3)
minimum	0	0	6.1	6.1	0
median	21.34	12.5	64.9	26.55	33.8
maximum	708.11	627.64	439.4	142.6	708.1
Number of sites	18	34	35	10	97
Distance to City Center (m)					
Mean (sd)	1581.6 (795)	7901.69 (4049)	3564.1 (2194)	892.9 (622)	4441.2 (3854.6)
minimum	0	861	510.2	34.1	0
median	1641.53	7346.7	3057.8	789.35	3009.5
maximum	2639.32	199955.9	9221.5	1850.7	19955.9
Number of sites	18	34	35	10	97
Distance to Water (m)					
Mean (sd)	1027 (522)	2508.27 (1727)	819.17 (491)	157.69 (110)	1381.6 (1380.5)
minimum	52.43	191.72	71.9	17.1	17.1
median	1031.59	2349.64	804.5	130.6	976.9
maximum	1915.12	6035.04	2237	368.2	6035
Number of sites	18	34	35	10	97
Bird Biodiversity Metrics					
Species Richness					
Mean (sd)	11.5 (4.15)	14.44 (4.18)	21.03 (6.52)	23.9 (4.12)	17.2 (6.7)
minimum	5	6	3	17	3
median	11.5	14.5	20	24.5	17
maximum	20	21	35	30	35
Number of sites	18	34	35	10	97
Simpson Evenness					
Mean (sd)	0.06 (0.02)	0.05 (0.01)	0.05 (0.07)	0.03 (0.01)	0.1 (0)
minimum	0.03	0.03	0.02	0.03	0
median	0.06	0.05	0.03	0.03	0
maximum	0.11	0.09	0.4	0.05	0.4
Number of sites	18	34	35	10	97
Average # of Individuals					
Mean (sd)	35.72 (17.5)	41.07 (29.1)	34.55 (11.7)	50.04 (23.8)	38.6 (21.7)
minimum	6.25	29.13	18.8	15.4	6.2
median	34.88	13.25	31	44.9	33
maximum	83.25	32	62.6	89	127.8
Number of sites	18	34	35	10	97

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