

UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL  
INSTITUTO DE BIOCÊNCIAS  
PROGRAMA DE PÓS-GRADUAÇÃO EM ECOLOGIA

Tese de Doutorado

**Distribuição e tamanho populacional de papagaios (*Amazona spp.*) da Mata Atlântica: uma análise estatística com integração de dados**

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Porto Alegre, setembro de 2021.

Distribuição e tamanho populacional de papagaios (*Amazona spp.*) da Mata Atlântica: uma análise estatística com integração de dados

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Tese de Doutorado apresentada ao Programa de Pós-Graduação em Ecologia, do Instituto de Biociências da Universidade Federal do Rio Grande do Sul, como parte dos requisitos para obtenção do título de Doutor em Ciências com ênfase em Ecologia.

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Porto Alegre, setembro de 2021.

### CIP - Catalogação na Publicação

Zulian, Viviane  
Distribuição e tamanho populacional de papagaios  
(Amazona spp.) da Mata Atlântica: uma análise  
estatística com integração de dados / Viviane Zulian.  
-- 2021.  
82 f.  
Orientador: Gonçalo Ferraz.

Tese (Doutorado) -- Universidade Federal do Rio  
Grande do Sul, Instituto de Biociências, Programa de  
Pós-Graduação em Ecologia, Porto Alegre, BR-RS, 2021.

1. Psittacidae. 2. modelos de ocupação de sítios.  
3. N-mixture models. 4. integração de dados. 5.  
espécies ameaçadas. I. Ferraz, Gonçalo, orient. II.  
Título.

*Dedico essa tese a todas aquelas mulheres que foram impedidas de seguirem seus sonhos simplesmente por serem mulheres, em especial minha mãe e minhas avós.*

## AGRADECIMENTOS

Os quatro anos de doutorado representam muito mais do que os três capítulos que estão nessa tese. Eles representam o amadurecimento pessoal e profissional, o aprendizado e as amizades que construí. Fica a certeza de que o caminho fica muito mais divertido e menos difícil quando aparecem mãos oferecendo ajuda. Por isso, agradeço:

- Ao meu orientador, Gonçalo Ferraz, por todo o treinamento, a ajuda no campo e no laboratório, as discussões e apoio de sempre. Obrigada por sempre acreditar em mim!
- Ao David Miller, pela recepção durante meu período nos Estados Unidos e pelas discussões e treinamento estatístico.
- Aos colegas do Laboratório de Biologia de Populações e, em especial, ao André pelas discussões e a Sara, pela parceria e ajuda em campo.
- À Eliara Muller, que desde 2011 tem me ajudado, apoiado e acreditado no meu trabalho.
- Às mulheres maravilhosas que são refúgio, tanto para os dias de tristeza quanto para os de alegria: Deizi, Maiara, Aline, Daniela, Paula, Luiza, Patrícia, Michelle, Iara, Flora, Kauane, Bianca. Aos demais amigos do RolEco: obrigada por serem o melhor grupo de apoio que eu poderia ter!
- Ao PPG Ecologia, à CAPES pelas bolsas de doutorado e de doutorado-sanduíche.
- A todos os observadores de aves que adicionam suas observações nas plataformas de ciência cidadã. Esse trabalho também é de vocês! Muito obrigada!
- Ao Reinaldo Guedes, administrador do WikiAves, por disponibilizar os dados. Esse trabalho não teria sido possível sem você!
- Aos pesquisadores do Proyecto Selva Pino Paraná (especialmente Kristina Cockle), Guyra Paraguay (especialmente Arne Lesterhuis) e Projeto Charão (especialmente Nêmora Prestes e

Jaime Martinez) por disponibilizarem os dados de contagens de *Amazona vinacea*.

- À Rufford Foundation, o Funbio e o Instituto Humanize por acreditarem nesse projeto e terem financiado as atividades de campo.

- À Madeireira Palma Sola S/A e ao Grupo Grimpeiro pelo apoio logístico.

- A todos os voluntários que me auxiliaram no trabalho de campo.

- Aos moradores do oeste de Santa Catarina, pela recepção calorosa durante minhas atividades de campo.

- À toda minha família, pelo apoio e amor incondicional, em especial meus pais Gilmar e Clarice e meu irmão Cristian. Essa conquista também é de vocês e não teria sido possível sem vocês!

Muito obrigada! Amo todos!

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## 1. RESUMO

Abundância e área de distribuição são duas variáveis de estado cruciais para entendimento das populações, bem como para a categorização de ameaça das espécies pela IUCN. Nesse trabalho, focamos a atenção em quatro espécies da família Psittacidae—uma das mais ameaçadas dentre as aves—*Amazona brasiliensis*, *A. pretrei*, *A. rhodocorytha* e *A. vinacea*. No primeiro capítulo, estimamos o tamanho populacional global de *A. vinacea* a partir de contagens replicadas e discutimos as fontes de incerteza associadas às contagens e estimativas e como minimizá-las. No segundo capítulo, mapeamos a área de distribuição global de *A. vinacea* a partir de integração de dados de pesquisa com dados de plataformas de ciência cidadã e discutimos como levar em consideração as especificidades de cada conjunto de dados, o esforço amostral, as covariáveis de sítio e a autocorrelação espacial nas análises. No terceiro capítulo, reunimos toda a informação disponível na literatura sobre o tamanho populacional das espécies *A. brasiliensis*, *A. pretrei*, *A. rhodocorytha* e *A. vinacea*, e mapeamos a área distribuição para cada espécie. Dentre as quatro espécies estudadas, *A. pretrei* possui a série temporal mais longa de monitoramento e as maiores contagens—em torno de 20.000 indivíduos. *A. vinacea* é a única espécie com uma estimativa estatística do tamanho populacional—em torno de 8.500 indivíduos para 2017. O tamanho das áreas estimadas variou de 15.000 km<sup>2</sup> para *A. brasiliensis* até 434.000 km<sup>2</sup> para *A. vinacea*. *A. rhodocorytha* é a espécie que mais urgentemente necessita de estudos de tamanho populacional, já que não conta com programa de monitoramento. O uso de dados de ciência cidadã se mostrou uma ferramenta muito útil para mapeamento de distribuição de espécies. Entretanto, para obter estimativas mais informativas, é crucial que a amostragem e análises levem em consideração a incerteza associada à essas estimativas.

**Palavras-chave:** modelos *N-mixture*, modelos de ocupação, integração de dados, Psittacidae, espécies ameaçadas.



## 2. ABSTRACT

Population size and geographic range are key predictors of extinction risk and are critical to listing species in IUCN threat categories. Here we focused our attention on four Psittacidae species one of the most threatened bird families *Amazona brasiliensis*, *A. pretrei*, *A. rhodocorytha*, and *A. vinacea*. In the first chapter, we estimated the *A. vinacea*'s global population size based on replicated counts. We discussed the uncertainty sources associated with the counts and estimates and how to minimize them. In the second chapter, we map the *A. vinacea*'s geographic range based on the integration of research-based data with citizen-science datasets and we demonstrate how to include the sampling effort information, spatial autocorrelation, and site covariates to obtain more precise and more accurate estimates. In the third chapter, we compiled abundance estimates and counts and estimated the geographic range of species *A. brasiliensis*, *A. pretrei*, *A. rhodocorytha* e *A. vinacea*. Comparing the four species, *A. pretrei* is the one with the longest time series of roost counts e the highest counts (~20,000 individuals). *A. vinacea* is the only species with a statistical estimate of abundance (~8,500 individuals). Estimated range areas varied from 15,000 km<sup>2</sup> for *A. brasiliensis* to 434,000 km<sup>2</sup> for *A. vinacea*. *A. rhodocorytha* is the species that most urgently need studies about population size and geographic range. The integration of citizen-science datasets with research data is a useful tool to map the geographic range of species. However, to obtain more informative estimates, it is crucial that the sampling and the analysis considering the uncertainty associated with the estimates.

**Keywords:** N-mixture models, occupancy models, data integration, Psittacidae, endangered species.

### 3. INTRODUÇÃO GERAL

Abundância e distribuição são as duas variáveis de estado mais importantes para caracterização de populações (Gaston, 1994; Norris, 2004). Essas variáveis estão diretamente relacionadas com o risco de extinção (Lawton, 1995) e são informações fundamentais para o manejo e conservação das espécies (Caughley, 1994; Norris, 2004). Além disso, são incluídas de forma direta, em quatro dos cinco critérios utilizados atualmente pela *International Union for Conservation of Nature* (IUCN) para definição das categorias de ameaça das espécies (Mace et al., 2008). Apesar da importância de conhecer a abundância e distribuição das espécies, a obtenção de estimativas acuradas geralmente exige coleta de dados em áreas extensas e envolve alto custo para monitoramento. A falta de recursos financeiros e a dificuldade em amostrar têm limitado o conhecimento, não só da distribuição geográfica (Jetz et al., 2012), mas também da abundância das espécies.

As amostragens de uma população estão sujeitas à falhas. Dois números diferentes, oriundos de duas contagens da mesma população em diferentes momentos não significam, necessariamente, alteração na abundância da espécie. Da mesma forma, a não-detecção de uma espécie em um local não representa uma ausência verdadeira. A discriminação entre alteração na abundância ou ocorrência verdadeiras e variação ao acaso nas contagens ou detecções só é possível através da quantificação da incerteza associada a essas estimativas. Levantamentos planejados com amostras replicadas de um conjunto predeterminado de locais usando protocolos padronizados que observam a presença ou ausência e número de indivíduos de espécies-alvo fornecem informações de alta qualidade, mas são raros. Por outro lado, plataformas de ciência cidadã, como o eBird (Sullivan et al., 2009), o Xeno-canto (Xeno-canto, 2019) e o WikiAves (WikiAves, 2019) têm ganhado popularidade. Pelo fato de armazenarem milhares de registros de espécies de aves,

conjuntos de dados oriundos de plataformas de ciência cidadã têm o potencial de preencher lacunas no conhecimento sobre a distribuição e abundância das espécies (Altwegg & Nichols, 2018; La Sorte & Somveille, 2020; Sullivan et al., 2017).

Dentre os grupos animais que mais urgentemente necessitam de estudos sobre abundância e distribuição, a família Psittacidae—a maior família entre as aves não-passeriformes—destaca-se, pois apresenta o maior número absoluto de espécies ameaçadas entre as aves, segundo a IUCN (BirdLife International, 2021). A perda de hábitat e a retirada de filhotes de ninhos são os principais fatores causando o declínio da abundância dessas espécies (Collar & Juniper, 1992; Juniper & Parr, 1998). Por serem dependentes de ambientes florestais, a maioria dos psitacídeos utiliza cavidades naturais para reproduzir (Juniper & Parr, 1998) e são impactados diretamente pela destruição das florestas (Collar & Juniper, 1992) e corte seletivo de árvores (Cockle et al., 2010), causados principalmente pela expansão agroindustrial (Berkunsky et al., 2017; Foley, 2005). A retirada de filhotes de ninhos afeta principalmente as espécies maiores, as mais coloridas, mais fáceis de capturar e as mais valorizadas no comércio ilegal (Tella & Hiraldo, 2014; Wright et al., 2001).

O gênero *Amazona*, grupo dos papagaios, é o mais diverso dentro da família Psittacidae, possuindo 36 espécies distribuídas desde o norte da Argentina até o norte do México (BirdLife International, 2021). Metade das espécies (18) estão ameaçadas em nível global e 25 delas apresentam declínio populacional, segundo a lista vermelha da IUCN (BirdLife International, 2021). A retirada de filhotes de ninhos foi reportada por Wright et al. (2001) como a principal causa de mortalidade para quatro espécies: *A. vinacea*, *A. kawalli*, *A. ochrocephala*, e *A. auropalliata*. A perda de hábitat é também uma ameaça para o gênero, especialmente em biomas onde o desmatamento é mais intenso, como na Mata Atlântica. Hábitat para sete espécies de

papagaios (del Hoyo et al., 2017), a Mata Atlântica é a segunda maior floresta na América do Sul (Ribeiro et al., 2011; Tabarelli et al., 2010) e um *hotspot* de biodiversidade (Ribeiro et al., 2011). Entretanto, o bioma perdeu quase 90% da sua cobertura original desde a chegada dos europeus e apenas 1% da sua extensão original está incluída em áreas protegidas (Ribeiro et al., 2009). Considerando o efeito do uso da terra nas populações de papagaios na Mata Atlântica (Vergara-Tabares et al., 2020), bem como a importância do gênero *Amazona* dentro da família Psittacidae, buscamos nesta tese entender a distribuição e tamanho populacional das quatro espécies de papagaios mais emblemáticas da Mata Atlântica: *A. brasiliensis*, *A. rhodocorytha*, *A. vinacea*, e *A. pretrei*. Estas são espécies endêmicas da Mata Atlântica (Vale et al., 2018) e classificadas pela IUCN como Quase-ameaçada, Vulnerável, Em perigo e Vulnerável, respectivamente.

Para entender a distribuição e tamanho populacional das quatro espécies de papagaios endêmicas da Mata Atlântica, integramos dados de diferentes fontes. No capítulo 1, estimamos a abundância global de *A. vinacea* a partir de contagens da população realizadas por diferentes grupos de pesquisa em dormitórios conhecidos ao longo da distribuição da espécie. Nesse capítulo, discutimos também as fontes de incerteza associadas à estimativa de abundância e como minimizá-las a partir do delineamento amostral e análise estatística. No capítulo 2, utilizamos modelos de ocupação de sítios com integração de dados de pesquisa e de plataformas de ciência cidadã (eBird, WikiAves e Xeno-canto) para mapear a distribuição de *A. vinacea*. Neste capítulo, mostramos como incluir integração de dados, covariáveis de amostragem, covariáveis de sítio e autocorrelação espacial gera mapas mais acurados e precisos da distribuição da espécie em comparação a modelos que não incluem todos esses fatores. No capítulo 3, reunimos toda a informação disponível sobre distribuição e tamanho populacional para as quatro espécies de papagaios: *A. brasiliensis*, *A. rhodocorytha*, *A. vinacea*, e *A. pretrei*. A partir de dados de pesquisa e plataformas de ciência

cidadã, mapeamos a distribuição das quatro espécies e, a partir de dados disponíveis na literatura, discutimos como o número de indivíduos de cada espécie mudou ao longo do tempo. A atualização no status do conhecimento sobre distribuição e tamanho populacional das quatro espécies na Mata Atlântica contribui para definição de esforços futuros de monitoramento e conservação, além de servir como base para categorização de ameaça das espécies pela IUCN. Além disso, os métodos de análise envolvendo integração de dados desenvolvidos nesta tese poderão ser aplicados para outros grupos de animais, contribuindo para melhor conhecimento sobre distribuição e abundância.

#### 4. REFERÊNCIAS

- Alonso, H. G. (2001). Conductas de gregarismo y vocalización de la cotorra cubana (*Amazona leucocephala*). *Ornitologia Neotropical*, 141–152.
- Altwegg, R., & Nichols, J. D. (2018). Occupancy models for citizen-science data. *Methods in Ecology and Evolution*, 10(1), 8–21. <https://doi.org/10.1111/2041-210X.13090>
- Berg, K. S., & Angel, R. R. (2006). Seasonal roosts of Red-lored Amazons in Ecuador provide information about population size and structure. *Journal of Field Ornithology*, 77(2), 95–103. <https://doi.org/10.1111/j.1557-9263.2006.00028.x>
- Berkunsky, I., Quillfeldt, P., Brightsmith, D. J., Abbud, M. C., Aguilar, J. M. R. E., Alemán-Zelaya, U., Aramburú, R. M., Arce Arias, A., Balas McNab, R., Balsby, T. J. S., Barredo Barberena, J. M., Beissinger, S. R., Rosales, M., Berg, K. S., Bianchi, C. A., Blanco, E., Bodrati, A., Bonilla-Ruz, C., Botero-Delgadillo, E., ... Masello, J. F. (2017). Current threats faced by Neotropical parrot populations. *Biological Conservation*, 214, 278–287. <https://doi.org/10.1016/j.biocon.2017.08.016>
- BirdLife International. (2021). *The IUCN Red List of Threatened Species*. [www.iucnredlist.org](http://www.iucnredlist.org)

- Caughley, G. (1994). Directions in Conservation Biology. *The Journal of Animal Ecology*, 63(2), 215. <https://doi.org/10.2307/5542>
- Cockle, K. L., Martin, K., & Drever, M. C. (2010). Supply of tree-holes limits nest density of cavity-nesting birds in primary and logged subtropical Atlantic forest. *Biological Conservation*, 143(11), 2851–2857. <https://doi.org/10.1016/j.biocon.2010.08.002>
- Collar, N. J., & Juniper, A. T. (1992). Dimensions and Causes of the Parrot Conservation Crisis. In *New World parrots in crisis: Solutions from conservation biology*. Smithsonian Institution Press.
- Cougill, S., & Marsden, S. J. (2004). Variability in roost size in an Amazona parrot: Implications for roost monitoring. *Journal of Field Ornithology*, 75(1), 67–73. <https://doi.org/10.1648/0273-8570-75.1.67>
- del Hoyo, J., Elliott, A., Sargatal, J., Christie, D. A., & Juana, E. de. (2017). *Handbook of the Birds of the World Alive*. Lynx Edicions. <http://www.hbw.com/node/54755>
- Foley, J. A. (2005). Global Consequences of Land Use. *Science*, 309(5734), 570–574. <https://doi.org/10.1126/science.1111772>
- Gaston, K. J. (1994). *Rarity*. Chapman & Hall. <https://doi.org/10.1007/978-94-011-0701-3>
- Jetz, W., McPherson, J. M., & Guralnick, R. P. (2012). Integrating biodiversity distribution knowledge: Toward a global map of life. *Trends in Ecology & Evolution*, 27(3), 151–159. <https://doi.org/10.1016/j.tree.2011.09.007>
- Juniper, T., & Parr, M. (1998). *Parrots: A guide to the parrots of the World*. Yale University Press.
- La Sorte, F. A., & Somveille, M. (2020). Survey completeness of a global citizen-science database of bird occurrence. *Ecography*, 43, 34–43.

- Lawton, J. H. (1995). Population dynamic principles. In J. H. Lawton & R. M. May (Eds.), *Extinction Rates* (pp. 147–163). Oxford University Press.
- Mace, G. M., Collar, N. J., Gaston, K. J., Hilton-Taylor, C., AkçAkaya, H. R., Leader-Williams, N., Milner-Gulland, E. J., & Stuart, S. N. (2008). Quantification of Extinction Risk: IUCN's System for Classifying Threatened Species. *Conservation Biology*, 22(6), 1424–1442.
- Martinez, J., & Prestes, N. P. (2008). Tamanho populacional, tamanho médio de bando e outros aspectos demográficos do papagaio-charão (*Amazona pretrei*). In J. Martinez & N. P. Prestes (Eds.), *Biologia da conservação: Estudo de caso com papagaio-charão e outros papagaios brasileiros*. UPF Editora.
- Moura, L. N. de, Vielliard, J. M. E., & da Silva, M. L. (2010). Seasonal Fluctuation of the Orange-winged Amazon at a Roosting Site in Amazonia. *The Wilson Journal of Ornithology*, 122(1), 88–94. <https://doi.org/10.1676/09-013.1>
- Norris, K. E. N. (2004). Managing threatened species: The ecological toolbox, evolutionary theory and declining-population paradigm. *Journal of Applied Ecology*, 41(3), 413–426.
- Ribeiro, M. C., Martensen, A. C., Metzger, J. P., Tabarelli, M., Scarano, F. R., & Fortin, M.-J. (2011). The Brazilian Atlantic Forest: A Shrinking Biodiversity Hotspot. In F. E. Zachos & J. C. Habel (Eds.), *Biodiversity Hotspots*. Springer Berlin Heidelberg. <https://doi.org/10.1007/978-3-642-20992-5>
- Ribeiro, M. C., Metzger, J. P., Martensen, A. C., Ponzoni, F. J., & Hirota, M. M. (2009). The Brazilian Atlantic Forest: How much is left, and how is the remaining forest distributed? Implications for conservation. *Biological Conservation*, 142(6), 1141–1153. <https://doi.org/10.1016/j.biocon.2009.02.021>

- Sullivan, B. L., Phillips, T., Dayer, A. A., Wood, C. L., Farnsworth, A., Iliff, M. J., Davies, I. J., Wiggins, A., Fink, D., Hochachka, W. M., Rodewald, A. D., Rosenberg, K. V., Bonney, R., & Kelling, S. (2017). Using open access observational data for conservation action: A case study for birds. *Biological Conservation*, 208, 5–14. <https://doi.org/10.1016/j.biocon.2016.04.031>
- Sullivan, B. L., Wood, C. L., Iliff, M. J., Bonney, R. E., Fink, D., & Kelling, S. (2009). eBird: A citizen-based bird observation network in the biological sciences. *Biological Conservation*, 142(10), 2282–2292. <https://doi.org/10.1016/j.biocon.2009.05.006>
- Tabarelli, M., Aguiar, A. V., Ribeiro, M. C., Metzger, J. P., & Peres, C. A. (2010). Prospects for biodiversity conservation in the Atlantic Forest: Lessons from aging human-modified landscapes. *Biological Conservation*, 143(10), 2328–2340. <https://doi.org/10.1016/j.biocon.2010.02.005>
- Tella, J. L., & Hiraldo, F. (2014). Illegal and Legal Parrot Trade Shows a Long-Term, Cross-Cultural Preference for the Most Attractive Species Increasing Their Risk of Extinction. *PLoS ONE*, 9(9), e107546. <https://doi.org/10.1371/journal.pone.0107546>
- Vale, M. M., Tourinho, L., Lorini, M. L., Rajão, H., & Figueiredo, M. S. L. (2018). Endemic birds of the Atlantic Forest: Traits, conservation status, and patterns of biodiversity. *Journal of Field Ornithology*, 89(3), 193–206. <https://doi.org/10.1111/jof.12256>
- Vergara-Tabares, D. L., Cordier, J. M., Landi, M. A., Olah, G., & Nori, J. (2020). Global trends of habitat destruction and consequences for parrot conservation. *Global Change Biology*, 26(8), 4251–4262. <https://doi.org/10.1111/gcb.15135>
- WikiAves. (2019). *WikiAves, a Enciclopédia das Aves do Brasil*. <http://www.wikiaves.com.br>



Wright, T. F., Toft, C. A., Enkerlin-Hoeflich, E., Gonzalez-Elizondo, J., Albornoz, M., Rodríguez-Ferraro, A., Rojas-Suárez, F., Sanz, V., Trujillo, A., Beissinger, S. R., A., V. B., A., X. G., Brice, A. T., Joyner, K., Eberhard, J., Gilardi, J., Koenig, S. E., Stoleson, S., Martuscelli, P., ... Wiley, J. W. (2001). Nest Poaching in Neotropical Parrots. *Conservation Biology*, 15(3), 710–720. <https://doi.org/10.1046/j.1523-1739.2001.015003710.x>

Xeno-canto. (2019). Xeno-Canto: Bird Sounds from around the World. <https://www.xeno-canto.org/>

**5. CAPÍTULO 1: Addressing multiple sources of uncertainty in the estimation of global parrot abundance from roost counts: A case study with the Vinaceous-breasted Parrot (*Amazona vinacea*)**

Artigo publicado na revista *Biological Conservation*.



## Addressing multiple sources of uncertainty in the estimation of global parrot abundance from roost counts: A case study with the Vinaceous-breasted Parrot (*Amazona vinacea*)

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### ARTICLE INFO

#### Keywords:

Endangered species  
Imperfect detection  
N-mixture model  
Psittacidae  
Roost count  
Vinaceous-breasted parrot

### ABSTRACT

Population size is a key predictor of extinction risk and is critical to listing species in IUCN threat categories. Assessing population size can be particularly difficult for gregarious species, such as parrots—one of the most threatened bird families—whose ecology and behavior generate multiple sources of uncertainty that need to be addressed in monitoring efforts. To improve estimates of abundance for the endangered Vinaceous-breasted Parrot (*Amazona vinacea*), we combined extensive roost counts over the global range of the species (Argentina, Paraguay, Brazil) with an intensive regional survey designed to address five sources of uncertainty about parrot abundance in western Santa Catarina state (WSC), Brazil, in 2016 and 2017. We estimated abundance at both regional and whole-range scales using N-mixture models of replicated count data, which account for imperfect detection. The regional-scale estimate was  $1826 \pm 236$  and  $1896 \pm 105$  individuals for 2016 and 2017, respectively; global abundance was estimated at  $7789 \pm 655$  and  $8483 \pm 693$  individuals for the same two years. We found no statistical evidence of population change at either scale of the analysis. Although our assessments of abundance and geographic range are larger than those currently reported by the IUCN, we suggest the Vinaceous-breasted Parrot should remain in the 'Endangered' IUCN threat category pending further investigation of population trends. We recommend that roost-monitoring programs for parrots consider and address sources of uncertainty through adequate field protocols and statistical analyses, to better inform assessments of population size, trends, and threat status.

### 1. Introduction

Population size is arguably the most important state variable in population biology (Gaston, 1994); along with range size, it is the best predictor of extinction risk (Lawton, 1995) and plays a central role in population management (Caughley, 1994; Norris, 2004). Abundance is directly implicated in three of the five IUCN (International Union for the Conservation of Nature) criteria for listing species in threat

categories (Mace et al., 2008). Among the animal groups in most urgent need of abundance information, parrots (Psittaciformes) stand out for having the highest number of threatened species of all non-passerine bird orders (Olah et al., 2016). Of 394 extant species of parrots, 117 (29%) are listed as threatened, and 81 of these are declining, according to the IUCN (BirdLife International, 2020). The key causes of parrot population decline are habitat loss—due to deforestation and agroindustrial expansion—, and nest poaching—due to illegal pet trade

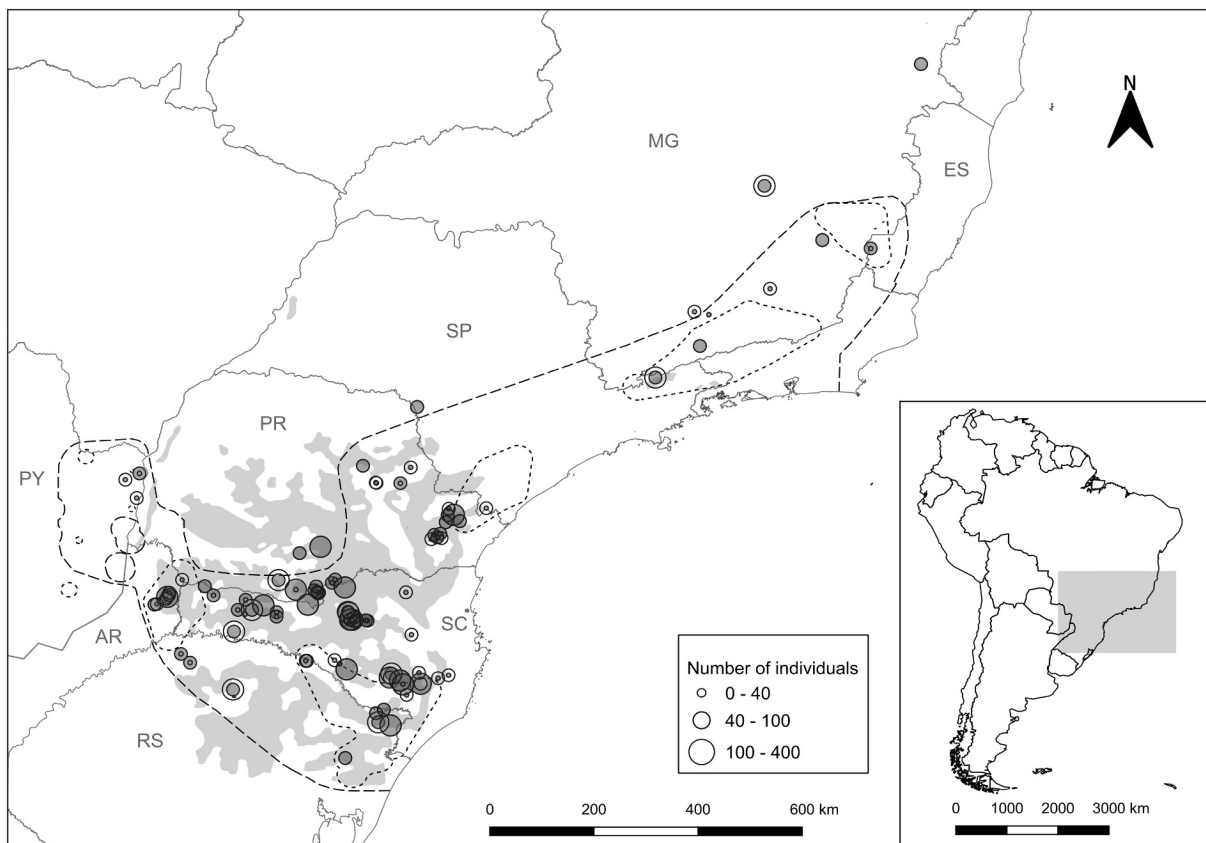
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<https://doi.org/10.1016/j.biocon.2020.108672>

Received 18 October 2019; Received in revised form 8 April 2020; Accepted 12 June 2020

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**Fig. 1.** Estimated number of Vinaceous-breasted Parrots per roost (circles), hypothetical IUCN range areas (dashed polygons), and potential extent of *Araucaria angustifolia* forests (gray polygon). Concentric circles show estimates from 2016 (gray) and 2017 (empty), with sizes corresponding to the abundance classes shown in the legend. When the estimates from both years fall in the same class, the superimposed circles appear as a single gray circle. The set of short-dash polygons represent the IUCN 'Extant' range, while the single, larger, long-dash polygon represents the IUCN 'Possibly Extant' range. Gray, upper-case labels indicate Paraguay (PY), the Argentinian province of Misiones (AR), and the six Brazilian states mentioned in the text: Espírito Santo (ES), Minas Gerais (MG), São Paulo (SP), Paraná (PR), Santa Catarina (SC), and Rio Grande do Sul (RS).

(Berkunsky et al., 2017; Olah et al., 2016; Wright et al., 2001). However, statistical estimates of parrot population size remain difficult to obtain and are available for very few species (Dénes et al., 2018; Marsden and Royle, 2015).

The globally endangered Vinaceous-breasted Parrot (VBP; *Amazona vinacea*) is restricted to the Atlantic Forest biome, mostly within Brazil but with small areas of occurrence in the Argentinian province of Misiones and eastern Paraguay (Carrara et al., 2008; Cockle et al., 2007; Prestes et al., 2014; Segovia and Cockle, 2012; Fig. 1). VBPs appear to be associated with the ancient Paraná Pine (*Araucaria angustifolia*; Cockle et al., 2019; Collar et al., 2017; Tella et al., 2016), but they also forage and nest in other trees (Bonaparte and Cockle, 2017; Cockle et al., 2007; Prestes et al., 2014), and their incompletely known geographic range extends beyond the current range of *Araucaria* forests (Carrara et al., 2008; Cockle et al., 2007; Collar et al., 2017). As with many other parrot species, incomplete knowledge about the VBP geographic range and population size results in part from movements associated with temporal variation in food availability (Renton et al., 2015; Webb et al., 2014). Seasonal movements reportedly coincide with the fruiting of *Ocotea puberula*, *Podocarpus lambertii*, *Vitex megapotamica*, Juçara palms (*Euterpe edulis*), and *Araucaria* pines (Collar et al., 1992; Forshaw, 2010; Prestes et al., 2014). Unpredictable movements make it difficult to anticipate where parrots will be, or whether parrots seen in different places are the same or different individuals, presenting interesting challenges to the estimation of population size. According to the IUCN, the extant geographic range of the VBP covers approximately 145,700 km<sup>2</sup> (BirdLife International and Handbook of the Birds of the World, 2016; Fig. 1). This range consists of

five major patches (>10,000 km<sup>2</sup>), and eleven relatively small patches (<1000 km<sup>2</sup>). Average distance between major patch centroids is 834 ± 379 km, revealing a discontinuous VBP distribution. Such discontinuity reflects not only the species' true range, but also the scarcity of information about population structure and movements. Accordingly, the IUCN recently updated the range map with a larger, 'possibly extant' layer that encloses all of the patches above (Fig. 1).

One traditional method to assess parrot abundance is to count individuals as they enter or leave communal roosts, a technique used for VBP over the last two decades (Casagrande and Beissinger, 1997; Abe, 2004; Coughill and Marsden, 2004; Cockle et al., 2007; Segovia and Cockle, 2012). Our field observations prior to this work suggest that, as in many parrot species, VBPs disperse in pairs across the species' range while courting and breeding (July–December), begin congregating in communal roosts towards the end of the breeding season (December–January), and may or may not continue to use these roosts throughout the entire non-breeding period (until June). As a result, during the January–June non-breeding period, the number of VBPs can vary from fewer than ten to hundreds of individuals, both among roosts and among days at the same roost (Abe, 2004; VZ, unpublished data). When August begins, there are virtually no parrots left at communal roosts and the population is once again dispersed across hundreds of nesting sites. Despite difficulties inherent to locating roosts and counting the number of individuals, roost counts remain one of the most popular and cost-effective ways of assessing the abundance of parrots (Matuzak and Brightsmith, 2007; Dénes et al., 2018).

Roost count design varies but always involves locating roosts, choosing the appropriate time for counting, and actually counting a

number that is as close as possible to the real number of animals present (Casagrande and Beissinger, 1997). In order to improve knowledge of the distribution and abundance of parrots from roost counts, one should approach the three tasks of locating, timing, and counting in a way that minimizes the magnitude of five key sources of uncertainty about the end result. Although we focus on one parrot species, the same sources of uncertainty arise for researchers assessing the abundance of other gregarious species, such as flamingos (Caziani et al., 2007) or bats (Mohd-Azlan et al., 2001; Walsh and Harris, 1996). The first and second sources have to do with locating roosts. First, there is uncertainty about the extent of the VBP's distribution. When does a gap in the range map represent true absence of the species vs. absence of observations? This problem is well represented by the difference between the IUCN 'Extant' and 'Possibly Extant' ranges in Fig. 1. The second source is uncertainty about density of roosts at the regional scale. At what point should one stop trying to find more roosts to free time for studying known roosts in detail? The third source of uncertainty concerns movement of individuals between roosts and constrains the timing of counts: if roosts correspond to isolated local populations, different roosts could be counted at any time throughout a non-breeding season. If, on the contrary, individuals move between roosts, researchers must account for such movements or count parrots at multiple roosts simultaneously. The fourth and fifth sources of uncertainty relate to the counting technique itself, and address, respectively, false positive and false negative observations of individuals. A false positive happens when by mistake a parrot is counted twice or more. A false negative happens when a parrot that is present at a site is not counted because it was overlooked.

This paper offers an assessment of VBP abundance for the years 2016 and 2017. We follow a two-pronged approach that combines data from two spatial scales, two counting techniques, and two research teams. At the regional scale, we estimate the number of VBPs in Western Santa Catarina/Brazil (WSC; Fig. 2) while seeking to address all five sources of uncertainty listed above. We chose to focus the regional research on WSC because a) being an area of intense agro-industrial activity with no previously published VBP observations, it has

been left out of the species' IUCN Extant map; b) it sits between two important VBP habitat areas in different countries (Misiones, in Argentina, and the *Araucaria* forests of Eastern Santa Catarina, in Brazil), and c) based on our previous experience, we expected to find roosts that were not yet documented in WSC. At the whole-range scale, we provide a global statistical estimate of the species based on counts of parrots observed in all VBP roosts known to us, throughout the entire range of the species.

## 2. Methods

### 2.1. Whole-range sampling

Whole-range sampling took place over 98 sites spanning an area from northern Minas Gerais, in the north, to northeastern Rio Grande do Sul, 1500 km to the south. The area extends west to, and includes eastern Paraguay, as well as the Argentinian province of Misiones (Fig. 1). Approximately one quarter (22) of the count sites are inside the IUCN Extant range of the VBP, with the remaining three quarters (76) outside. Sites correspond to regularly-used roosts and to points of frequent flyover by parrots at dawn and dusk (Supplemental Material Table S1). Our research team and collaborators identified the count sites, sometimes over decades of VBP observation (e.g. Cockle et al., 2007; Segovia and Cockle, 2012). All sites are located within the Atlantic Forest, defined by the southeast Atlantic portion of the 'tropical and subtropical moist broadleaf forest' eco-region of South America (Olson et al., 2001).

Sampling at the whole-range scale was carried out by 26 volunteer teams (Supplemental Material Table S1) coordinated by NPP and JM. Counts took place in 2016 (24–26 March in Argentina, 29 April to 15 May in Paraguay and Brazil) and 2017 (24 April to 15 May in Paraguay and Brazil only). Each team worked in areas that were familiar to its members, enabling us to cover most of the range in a short period and thus minimize the possibility of double-counting between sites. Of the total 98 sites, 33 were sampled only in 2016, 30 only in 2017, and 35 in both years (Supplemental Material Table S1). We visited sites once per

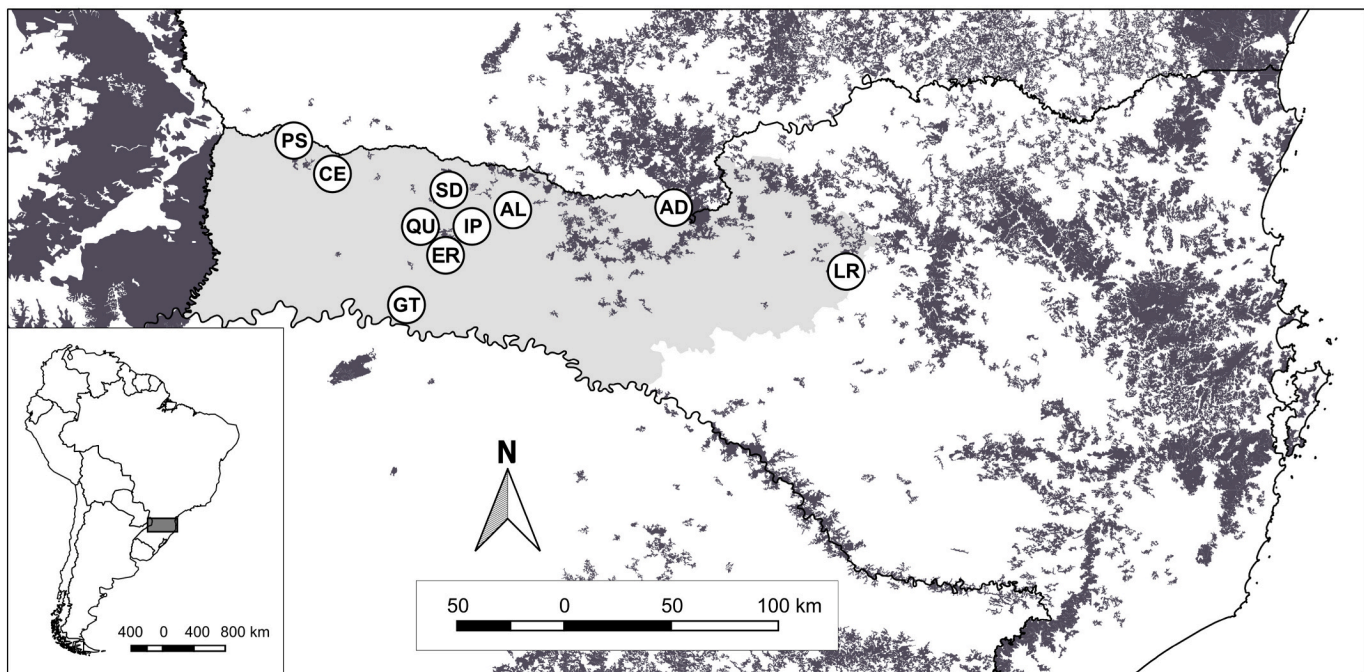


Fig. 2. Regional-scale study area of Western Santa Catarina (light gray). Dark gray indicates every patch of forest (excluding tree plantations)  $> 5 \text{ km}^2$  in area, according to the Brazilian Ministry of the Environment's *Mapa de Cobertura Vegetal dos Biomas Brasileiros* (MMA, 2007). Circles show the location of all presently known WSC roosts with their name abbreviations: PS (*Palma Sola*), CE (*Campo Erê*), GT (*Guatambu*), QU (*Quilombo*), SD (*São Domingos*), IP (*Ipuacu*), AL (*Abelardo Luz*), ER (*Entre Rios*), AG (*Água Doce*) and LR (*Lebon Régis*).

year, counting parrots at the beginning or at the end of the day. Counts started at dawn (30 min before sunrise) or dusk (90 min before sunset) and lasted until we could not detect parrot movement into or out of the roost for 20 min—which always happened within 2 h of the beginning of the count. The number of counting posts at each site varied between one and five, located at strategic points for observing movement of flying parrots in and out of the site area. Each count was performed by a team of one to ten observers who registered the number of parrots arriving or leaving the area, the flight direction, and the time. Whenever there was more than one post in a count, observers from different posts met at the end of the count to compare notes and agree on the minimum number of individual parrots seen.

## 2.2. Regional-scale sampling

The regional-scale study area is the western part of the Brazilian state of Santa Catarina (WSC; IBGE, 2015; Fig. 2), with approximately 100 by 300 km extending West-East between the Uruguay river (to the South) and the ridgeline that separates the Uruguay and Iguacú watersheds (to the North). Although mostly deforested, the area adjoins two large patches of forest habitat: the Atlantic Forest of Misiones, to the west, and the *Araucaria* forests of Eastern Santa Catarina, to the east (Fig. 2). WSC is remarkable for having a high frequency of VBP sightings by citizen scientists (Wikiaves, 2018) in an area that is almost entirely (88%) outside the IUCN extant range of the species (Fig. 1). WSC falls within the *Araucaria* forest and the Interior forest biogeographic sub-regions of the Atlantic Forest, which have lost, respectively, 87 and 93% of their forest cover since the onset of European colonization (Ribeiro et al., 2009). Nowadays, the remaining forest patches in WSC (Fig. 2) are surrounded by agro-industrial development, consisting mostly of soybean (*Glycine max*), eucalyptus (*Eucalyptus* sp.), and pine (*Pinus* sp.) plantations (Baptista and Rudel, 2006; Fearnside, 2001). The ten WSC sampling sites are a subset of the whole-range sites. They comprise all known VBP roosts in WSC and they all coincide with *Araucaria* forest patches >10 m tall. Four of the ten regional sites (*Guatambu*, *Campo Erê*, *Abelardo Luz* and *Água Doce*) have very open to non-existent vegetation under the *Araucaria* canopy (Fig. 2).

Fieldwork at the regional-scale was carried out by a single team coordinated by VZ and ESM. Here, we performed monthly visits to each site, across two consecutive non-breeding seasons: from December 2015 to July 2016, and from February to June 2017. By employing the same team for all roost counts of the same month in WSC, we could control and coordinate field technique much more tightly at the regional than at the whole-range scale. To avoid counting the same parrots twice in different roosts during the same month, each visit was performed in the shortest period possible—between four and ten days, depending on the number of roosts sampled. Each roost was sampled at dusk and at dawn of the next day, allowing us to visit two nearby roosts in the same twelve hour period. The shortest distance between roosts was 19 km and the longest single-day displacement recorded for radio-tagged VBPs is 17 km (Prestes et al., 2014). We moved between roosts at the average speed of 45 km per day; therefore, we find the possibility of double counting between roosts to be sufficiently small. In all, we completed 13 visits to WSC, eight during 2015–2016 and five during 2017. To minimize uncertainty about VBP distribution and roost density over the regional-scale, we spent one day per month searching for roosts and interviewing WSC residents that we met in the field. As we discovered new roosts, the number of roosts counted increased from four in December 2015 to five in February 2016, eight in May 2016, and ten in May 2017 (Fig. 2; Supplemental Material Table S2). The *Lebon Régis* and *Entre Rios* sites, also located in WSC, were only visited during the whole-range count of both years. In total, we completed 182 roost counts at the regional scale.

Regional-scale counts started at dusk (77) or dawn (105 counts), and lasted until we could no longer detect parrot movements, following the same times and criteria as described for the whole-range counts. We

visited every roost before the first count to establish observation posts in locations suitable for observing the arrival and departure of parrots. Each count was performed by a team of three observers (one per observation post), each equipped with a roost area map, a compass, an audio recorder, and a radio to communicate with team members about parrots going their way. Every time an observer saw one or more VBPs, she recorded the number of individuals, the time, and the direction of flight, as well as any other comments that could help understand the movement of the birds. At the end of each count, the team of three observers met to reconcile their notes and agree on one ‘most reasonable’ (MR) and one ‘highly conservative’ (HC) count result. The difference between MR and HC counts lies in how observers treat the possibility of double counting. Suppose, for example, that an observer sees five parrots arriving at a roost and a few minutes later sees another arrival of three individuals. Based on this information, the MR count is eight individuals. Suppose further, however, that one of the observers in the trio determined that there were unseen, but heard, parrots leaving the roost during the time between the two observations above. In this case, the team might judge that there was some, however small, possibility that the second group of three was a subset of the first group of five, which had exited the roost undetected and returned within sight. If that were the case, the HC count should be five and not eight, because five is the absolute minimum number of birds that the team is sure to have seen arriving at the roost.

The consideration of MR and HC counts addresses one source of uncertainty about VBP abundance estimates: the possibility that some animals may be counted more than once within one count. A second source of uncertainty is imperfect detection, i.e. the possibility that some animals are missed. To address imperfect detection, we replicated counts by working simultaneously with two teams of three observers, at the same roost and time, in ten of the thirteen sampling months. Simultaneous replication employed two observers (one from each team of three) per post, keeping sufficient distance between observers to preclude overhearing radio communications. Observers from different teams did not exchange any information about their observations until each team had separately agreed on its count results. We thus treat every team-specific count of a given roost and month, whether at dusk or dawn, as an independent sample of that roost for that month. When working with two teams counting at dusk and dawn we obtained the maximum of four replicate counts for one roost and month. Sometimes it rained and other times we didn't have a second team, but we had more than one count in 90% of the roost\*month combinations. The crucial difference between sampling designs at the regional- and whole-range scales was replication. At the regional-scale, we could afford and strove to replicate counts of the same roost and month as much as possible.

## 2.3. Data analysis

We modeled both regional and whole-range data using an N-mixture model approach (Royle, 2004). N-mixture models account for imperfect detection and estimate the number of individuals per site, given replicated count data. For each spatial scale, we summarized counts in an array  $C$  with dimensions  $S$  by  $R$  by  $M$ , where  $S$  is the number of roost sites,  $R$  is the maximum number of replicate counts per roost in any month, and  $M$  is the number of sampling months. Elements  $C_{ijk}$  of this array give the number of parrots counted in the  $j^{\text{th}}$  count of the  $i^{\text{th}}$  roost in the  $k^{\text{th}}$  month, with  $i = 1, \dots, S$ ,  $j = 1, \dots, R$ , and  $k = 1, \dots, M$ . The N-mixture model represents the true number  $N_{ik}$  of individuals in roost  $i$  and month  $k$  as drawn from a Poisson distribution with parameter  $\lambda_k$ . That is, the number of individuals per roost varies according to a Poisson distribution with mean  $\lambda_k$ , which itself varies through time. We account for imperfect detection by modeling the counts  $C_{ijk}$  as the result of a binomial sample with  $N_{ik}$  independent trials and probability of success  $p_k$ . In short, our models combine the biological variation of abundance among roosts with the sampling process of

parrot detection:

$$N_{ik} \sim \text{Poisson}(\lambda_k)$$

$$C_{ijk} \sim \text{Binomial}(N_{ik}, p_k).$$

When a roost  $i$  is not sampled in month  $k$ , we impute an estimate of  $N_{ik}$  based on the estimate of  $\lambda_k$  for that month. Such imputation accounts for the temporal variation in effort and implies that differences between abundance estimates from different months are not a result of variation in the number of roosts counted. In the way we set up the analysis, this imputation is a by-product of our Bayesian model fitting using MCMC methods (see below).

To analyze regional-scale data, we used two arrays  $C$ , of HC and MR counts, with dimensions  $S = 10$  sites,  $R = 4$  counts, and  $M = 13$  months. The first eight months correspond to December 2015 through July 2016, while the last five correspond to February–June 2017. Because our counts in WSC were often replicated at different times of the day, we modeled a binary effect of time of day (dawn vs. dusk) on  $\text{logit}(p)$ , to account for possible differences in visibility or parrot behavior between dawn and dusk counts. Models were fit in a Bayesian framework using gamma-distributed vague priors for  $\lambda$  and  $p$  parameters. We implemented models in the BUGS language (Lunn et al., 2000) running on JAGS (Plummer, 2003) with code adapted from Kéry and Royle (2016, chap. 6; Supplemental Material Appendix A). Regional-scale inference is based on draws from the posterior probability distribution of model parameters using an MCMC algorithm with three chains, 25,000 iterations and a burn-in stage of 5000 iterations.

Analysis of the whole-range data was based on the same model used for the regional scale, with some adjustments to model and data structure. We organized data into an array  $C$  with dimensions  $S = 98$  sites,  $R = 4$  counts, and  $M = 2$  ‘months’. The first ‘month’ of whole-range counts spans the period of late March to early May 2016, the second is May 2017. The main limitation of the whole-range data is lack of replicated counts within the same site and month outside WSC and one of the Misiones sites, i.e. in 87 out of 98 sites. While applying an N-mixture model to such data, we rely on information from only a few sites to infer detection probability everywhere else. This is not ideal but is the best we could do at present with the available data. To avoid demanding too much from limited information on detection we took two precautions. First, we simplified the detection model by estimating  $p$  as a constant value through time, across ‘months’. Second, we included environmental information—area of remaining *Araucaria* forest—as a covariate of  $\lambda$ . We measured *Araucaria* forest as standardized cover in a circular buffer with 17 km radius around each roost, which amounts to an area of 907 km<sup>2</sup>. We also tried buffer radiuses of 5 and 50 km in exploratory analyses, but elected to use a 17-km buffer because it corresponds to the longest single-day displacement recorded for radio-tagged VBPs (Prestes et al., 2014), and indeed resulted in the highest (positive) slope for the relationship between *Araucaria* cover and  $\lambda$ . *Araucaria* forest cover data resulted from the intersection of two maps: a map of the potential range of South American *Araucaria* Forest drawn by Hueck (1966) and georeferenced by Hasenack et al. (2017), and Ribeiro et al.’s (*in prep.*) map of existing Atlantic Forest remnants that are larger than 30-by-30 meters in area. To explore the consequences of the environmental covariate on our assessment of global population size, we built two alternative models, one without (*Model 1*) and the other with (*Model 2*) a year-dependent effect of *Araucaria* Forest cover on  $\lambda$ , the average roost population size. All regional-scale counts used in the whole range analysis were MR counts. As at the regional scale, we fit models in a Bayesian framework using vague priors. Whole-range inference was based on an MCMC algorithm with three chains, 50,000 iterations and a burn-in of 1000 iterations. At both regional and whole-range scales, we ran the MCMC until obtaining a value of the convergence criterion R-hat lower than 1.1 for all parameters.

To assess the Goodness of Fit (GoF) of our models, we applied leave-

one-out cross-validation (Conn et al., 2018) and a Bayesian  $p$ -value approach (Gelman et al., 1996) on a chi-squared discrepancy statistic  $T$ . For both the regional and the whole-range analysis, the former indicated that our models predicted the observed counts about right on average, but the latter indicated severe overdispersion. The Bayesian  $p$ -value, reflecting the frequency with which discrepancy is higher for replicated data ( $T_{\text{rep}}$ ) than for observed data ( $T_{\text{obs}}$ ), was zero for both analyses. This was not unexpected, since parrots often travel in pairs, thus violating the independence assumption of the model. To accommodate this, we had experimented with the beta-binomial variant of the model developed by Martin et al. (2011) and Dorazio et al. (2013) for group-living animals, which yielded acceptable GoF results, but completely unrealistic (too high) abundance estimates. This ‘good fit/bad prediction dilemma’ (Kéry and Royle, 2016) is observed not rarely with N-mixture models and so far does not have a formal remedy.

Thus, we had to decide between choosing an analysis that ignored detection error (e.g., some GLMM; Barker et al., 2018) and a simple N-mixture model that accommodates that key consideration when estimating abundance, but resulting in lack of fit, or overdispersion. We conducted a simple simulation (see Supplemental Material Appendix B), where we simulated replicated counts that resembled our data in the regional analysis. Our simulation randomly varied the degree of overdispersion at the site-level in both  $\lambda$  and  $p$ , and of site-by-occasion level in  $p$ . We then analysed the data set using an intercepts-only N-mixture model that ignored the resulting lack of fit and estimated the total population size. As an alternative,  $p$ -ignorant method we simply added up the maximum count across sites. We simulated 1000 data sets and found that the root mean squared error (RMSE) of the overdispersion-naive N-mixture model was 25% reduced compared to the  $p$ -ignorant method of adding maximum counts. This led us to choose the formal estimation method of the N-mixture model.

To accommodate the additional uncertainty stemming from the lack of fit or overdispersion detected in the GoF test, we chose an ad hoc way of increasing the uncertainty in our estimates by ‘stretching’ the posterior distributions around their mean. This was motivated by the frequent adoption of variance inflation by some overdispersion factor  $c$ -hat in frequentist analyses of count data, see e.g., Chapter 5 in Cooch and White (2020) for Cormack-Jolly-Seber models. We estimated the degree of overdispersion  $c$ -hat by the ratio  $T_{\text{obs}} / T_{\text{rep}}$ , from above, at 5.6 for the regional and 5.8 for the whole-range scale. To make the posterior distributions more dispersed, we first subtracted from all posterior samples of a parameter its mean, multiplied the result by our estimate of  $c$ -hat and then added back the original mean. All uncertainty assessments such as posterior SDs or credible intervals were then based on this ‘stretched’ sample of the posterior of a parameter. In our simulation, the coverage of this approach for total abundance summed across roosts was on average only 0.67 and thus considerably lower than the nominal level of 0.95, but much better than the coverage of ‘unstretched’ CRIs would have been. Therefore, to be conservative, we chose the stretching procedure despite its lack of theoretical underpinning.

### 3. Results

Comparison of most reasonable (MR) and highly conservative (HC) results from the regional-scale data suggest a small but consistent difference between counts. Whereas MR counts were always greater than or equal to HC counts of the same roost and month, they were also less variable between replicates within the same roost and month (Supplemental Material Table S2). Accordingly, estimates of detection probability ( $p$ ) tended to be higher for MR than for HC results; this was true in nine out of thirteen months for the whole WSC region (Table 1). Likewise, MR-based estimates of abundance tended to be more precise than their HC counterparts: roost and month-specific estimates based on MR counts were as precise or more precise than those based on HC counts in 95 of 130 cases (Supplemental Material Table S2). Spatial and

**Table 1**

Western Santa Catarina estimates of the number of Vinaceous-breasted Parrots ( $N$ ) in all known roosts and the average probability ( $p_{dawn}$ ) of detecting one parrot present at those roosts that were visited, at dawn, by month. Values preceded by the ‘ $\pm$ ’ sign are standard deviations of the posterior distribution of the parameter in question. Numbers in parentheses show the sum of the highest counts from each roost sampled in the corresponding month. MR and HC indicate estimates based on, respectively, ‘most reasonable’ and ‘highly conservative’ count results. Boldface numbers identify the highest  $N$  estimate of each year.

| Month         | 2015–2016                              |                 | 2017                                    |                 |
|---------------|--|-----------------|---|-----------------|
|               | $N$                                    | $p_{dawn}$      | $N$                                     | $p_{dawn}$      |
| December (MR) | 714 $\pm$ 92 (265)                     | 0.87 $\pm$ 0.06 |   |                 |
| (HC)          | 686 $\pm$ 106 (244)                    | 0.78 $\pm$ 0.08 |   |                 |
| January (MR)  | 1091 $\pm$ 190 (335)                   | 0.69 $\pm$ 0.10 |   |                 |
| (HC)          | 956 $\pm$ 183 (297)                    | 0.68 $\pm$ 0.12 |   |                 |
| February (MR) | <b>1826 <math>\pm</math> 236 (696)</b> | 0.67 $\pm$ 0.08 | 893 $\pm$ 90 (426)                      | 0.68 $\pm$ 0.06 |
| (HC)          | 1825 $\pm$ 270 (670)                   | 0.63 $\pm$ 0.09 | 754 $\pm$ 87 (374)                      | 0.70 $\pm$ 0.07 |
| March (MR)    | 1364 $\pm$ 100 (639)                   | 0.87 $\pm$ 0.03 | 1151 $\pm$ 121 (587)                    | 0.78 $\pm$ 0.08 |
| (HC)          | 1229 $\pm$ 99 (588)                    | 0.91 $\pm$ 0.03 | 1175 $\pm$ 176 (529)                    | 0.62 $\pm$ 0.10 |
| April (MR)    | 1482 $\pm$ 173 (562)                   | 0.61 $\pm$ 0.06 | 940 $\pm$ 98 (493)                      | 0.79 $\pm$ 0.08 |
| (HC)          | 1546 $\pm$ 218 (538)                   | 0.53 $\pm$ 0.07 | 859 $\pm$ 131 (418)                     | 0.70 $\pm$ 0.11 |
| May (MR)      | 1522 $\pm$ 166 (997)                   | 0.72 $\pm$ 0.10 | <b>1896 <math>\pm</math> 105 (1627)</b> | 0.76 $\pm$ 0.06 |
| (HC)          | 1755 $\pm$ 336 (965)                   | 0.55 $\pm$ 0.13 | 1693 $\pm$ 74 (1517)                    | 0.82 $\pm$ 0.05 |
| June (MR)     | 1397 $\pm$ 89 (761)                    | 0.80 $\pm$ 0.04 | 11,092 $\pm$ 121 (639)                  | 0.64 $\pm$ 0.07 |
| (HC)          | 1329 $\pm$ 91 (724)                    | 0.78 $\pm$ 0.04 | 1100 $\pm$ 161 (588)                    | 0.53 $\pm$ 0.09 |
| July (MR)     | 655 $\pm$ 96 (321)                     | 0.73 $\pm$ 0.09 |   |                 |
| (HC)          | 580 $\pm$ 90 (286)                     | 0.74 $\pm$ 0.10 |   |                 |

temporal variation is qualitatively similar between types of counts, with MR and HC counts resulting in the same maximum-abundance month (March 2017) and the same maximum-abundance roost (*Lebon Régis*). We also found a small but measurable effect of the time of day on detection probability, with dusk counts having detection probability on average 0.03 above dawn counts. The 95% credible interval of the negative ‘dawn’ coefficient excludes zero for both MR and HC data. For simplicity, we focus on MR results for any WSC-related content in the remainder of the paper.

Temporal variation in estimated abundance for WSC (summed across roosts) shows the lowest number of individuals in the two extremes of the non-reproductive period (Table 1): in December 2015, with an estimated 714  $\pm$  92 individuals (posterior mean  $\pm$  standard deviation), and in July 2016 with 655  $\pm$  96 individuals. The highest aggregate WSC count (1627 individuals) and  $N$  estimate (1896  $\pm$  105 individuals) were obtained in May 2017. Spatial variation among WSC roosts shows five of ten roosts – *Guatambu*, *Ipaçu*, *Abelardo Luz*, *Água Doce* and *Lebon Régis* – reaching  $N$  estimates in excess of 200 at some point during the sampling period. All roosts showed substantial variation in  $N$  between months in both years, but there was no obvious synchrony in the temporal variation of the number of individuals at different roosts. As with the highest estimates of  $N$ , the lowest were obtained in different months depending on roost. For example, while *Água Doce* peaked in March 2016 and May 2017, *Guatambu* did so in April 2016 and February 2017. *Abelardo Luz* was the only roost that

peaked both years in the same month, in June.

The posterior mean global abundance of VBPs varied slightly between models and years, but was always smaller than 10,000 individuals. *Model 1* estimated 7789  $\pm$  655 individuals (95% Bayesian credible interval 6586–9184) for 2016, and 8483  $\pm$  693 (7181–9977) for 2017. *Model 2* estimated 8012  $\pm$  714 individuals (6779–9507) for 2016, and 9039  $\pm$  779 (7641–10,677) for 2017. Estimates from *Model 2*, which includes a relationship between  $\lambda$  and *Araucaria* forest cover, were slightly higher than those from *Model 1*, but the 95% credible intervals from different models in the same year clearly overlap. Both counts and abundance estimates increased from 2016 to 2017, but there was overlap between 95% credible intervals of estimates from the same model in different years. The average probability of detecting a parrot that is present at a visited roost was 0.70  $\pm$  0.05 under *Model 1* and 0.67  $\pm$  0.05 under *Model 2*. There was a smaller difference between models within year than between years within model, but little statistical support for temporal change in global abundance. The positive effect (a logit-scale slope parameter) of *Araucaria* forest cover on  $\lambda$ , estimated by *Model 2*, differed between years and was higher in 2016 (0.43  $\pm$  0.04) than in 2017 (0.16  $\pm$  0.04). Such effects amount to a tripling of abundance as *Araucaria* cover increases from 20% to 80% of the buffer in 2016, but only to a 1.3-factor increase accompanying the same cover change in 2017.

The spatial distribution of *Model 1* abundance estimates across regions of the whole range (Table 2) reveals that Brazil accounted for

**Table 2**

Roosts visited, total number counted and Model 1 estimates of the number of Vinaceous-breasted Parrots in Argentina, Brazil, and Paraguay during the whole-range counts of 2016 and 2017. Estimates are given as mean  $\pm$  standard deviation of the posterior distribution. Dashes denote absence of counts in the corresponding location and year.

| Country   | Region            | 2016           |       |                | 2017           |       |                |
|-----------|-------------------|----------------|-------|----------------|----------------|-------|----------------|
|           |                   | Roosts visited | Count | M1 estimate    | Roosts visited | Count | M1 estimate    |
| Argentina | Misiones          | 7              | 252   | 426 $\pm$ 56   | 0              | –     | 605 $\pm$ 78   |
| Brazil    | Espírito Santo    | 0              | –     | 80 $\pm$ 23    | 1              | 2     | 28 $\pm$ 14    |
|           | Minas Gerais      | 5              | 58    | 336 $\pm$ 60   | 3              | 135   | 558 $\pm$ 70   |
|           | Paraná            | 16             | 803   | 2112 $\pm$ 198 | 17             | 805   | 2050 $\pm$ 205 |
|           | Rio Grande do Sul | 6              | 335   | 717 $\pm$ 75   | 9              | 409   | 642 $\pm$ 71   |
|           | Santa Catarina    | 28             | 2324  | 3860 $\pm$ 285 | 31             | 2606  | 4197 $\pm$ 296 |
|           | São Paulo         | 3              | 93    | 164 $\pm$ 27   | 2              | 109   | 247 $\pm$ 35   |
| Paraguay  | Alto Paraná       | 3              | 23    | 94 $\pm$ 27    | 2              | 18    | 156 $\pm$ 36   |
| Total     |                   | 68             | 3888  | 7789 $\pm$ 655 | 65             | 4084  | 8483 $\pm$ 693 |



>90% of the estimated population size in both years. The Brazilian state of Santa Catarina had the highest number of roosts (41), as well as the highest estimated population size of all Brazilian regions, accounting for 50% of the total population in both years. Paraná had the second highest estimates among regions, accounting for approximately 25% of the total population. Looking at the spatial variation of abundance estimates per roost, Santa Catarina came out on top again, with an average of 94 to 102 individuals per roost. The highest number of individuals estimated at one site was 380 in 2016 and 390 in 2017. The two estimates came from sites approximately 180 km apart, both in Santa Catarina and both in May, towards the end of the non-breeding season. The spatial distribution of *Model 2* estimates was qualitatively similar to that of *Model 1*. We focus on *Model 1* for simplicity and because it provides the most conservative abundance estimates.

#### 4. Discussion

We developed a counting technique and associated statistical analysis to estimate VBP abundance at two spatial scales: regional and whole-range. Our approach sought to address five sources of uncertainty about parrot abundance related to range limits, roost density, movement between roosts, false positive—these addressed by our count technique, and false negative observations—addressed by our statistical analysis. Based on estimates of abundance for 2016 and 2017, we provide evidence that the global VBP population consists of a few thousand, but definitely not more than ten thousand individuals. Comparison between global abundance estimates from the two years reveals that even though average estimates were greater in 2017 than in 2016 under both models, there is no statistical evidence that such increase resulted from population growth.

Global population estimates are approximately twice the maximum number of individuals counted in whole-range counts (Table 2). Since never >70% of the total known roosts were counted, summed counts are bound to result in underestimates of the global population size. Nonetheless, we strongly emphasize that our estimates do not warrant proposing a category change for the species. The IUCN assigns threat levels based on a combination of five criteria (Mace et al., 2008). In order to qualify for one level, a species must meet conditions from any of the five criteria for that level. Thus, non-fulfillment of one criterion does not warrant category change. More specifically, non-fulfillment of the conditions under criterion C (Small population size and decline) would require examination of range and population dynamic conditions under the other criteria, which are beyond the scope and possibilities of our two-year analysis of roost counts. We suggest that the species should remain in the 'Endangered' IUCN threat category pending demographic studies and analysis of the conditions under criteria A, B, D and E. Ideally, given appropriate coverage of the species range and understanding of population dynamics, one should be able to assess an extinction risk for the species, which is demanded by criterion E.

The assessment of extinction risk can only be as good as the underlying estimates of population size. Our regional and global estimates point out some of the ways in which researchers can address sources of uncertainty when monitoring VBP and other parrots. At the broadest level, there is uncertainty about species' ranges. We tried to reduce uncertainty about the VBP range by searching for new roosts 8 days/year in WSC, which returned a 150% increase in the number of sampling sites over the 2 years of the study. We covered the northern half of WSC in more detail than the southern half, which has only one known roost (*Guatambu*; Fig. 2), because it has more *Araucaria* forest and a higher density of large ( $\geq 5 \text{ km}^2$ ) forest patches; yet, judging from verbal reports and the distribution of sightings in WikiAves (Wikiaves, 2018) we believe there are more roosts to be found in the southern part of WSC. Only one-quarter of the counting sites in the whole-range counts were inside the IUCN range, showing that range uncertainty extends well beyond the limits of WSC (Fig. 1). The small areas suggestive of isolated populations in the IUCN Extant range (e.g., Fig. 1)

may be part of larger areas of continuous use and may be useful starting points for improving knowledge about the species' distribution.

From the abundance estimates and the spatial distribution of roosts, it appears that the number of both roosts and individuals per unit area increases towards the interior of the distribution range (Fig. 1). Roosts with more than one hundred individuals counted are located in the three southernmost states of Brazil, in agreement with the pattern of higher densities towards the center of species' ranges reported by Brown et al. (1995) and Gaston (2009). The non-homogenous density of individuals also appears related to the distribution of *Araucaria* forest cover, which is centered in southern Brazil (Fig. 1) and offers VBPs an important food source during the autumn and winter months (Collar et al., 2017; Prestes et al., 2014; Tella et al., 2016). *Model 2* results suggest that the relationship between *Araucaria* forest cover and parrot abundance may change substantially through time, as it decreased by >50% from 2016 to 2017. Such change is likely due to variability in the amount, spatial distribution and temporal distribution of *Araucaria angustifolia* seed production (Mantovani et al., 2004). When *Araucaria* seed production coincides with winter-scarcity of alternative resources, *Araucaria* could become a more important food source and a stronger driver of VBP distribution.

Spatiotemporal variability in environment and demography necessarily lead to temporal variation in VBP distribution. Such dynamism is evident in WSC from the disappearance of VBPs from roost sites during the breeding season, and from the variation in roost estimates throughout the study (Supplemental Material Table S2). We estimated the lowest numbers of VBPs during December 2015 and July 2016 (Table 1)—the first and last months of the sampling period of 2016. Nonetheless, temporal variation of abundance was far from synchronous across roosts (Supplemental Material Table S2). Indeed, estimates for *São Domingos* and *Abelardo Luz* were lowest in January and March of 2016, respectively, neither month being the first or last of the sampling period. If individuals were breeding in surrounding areas and aggregating at centrally-located roosts for the non-breeding season, we would expect a gradual accumulation of individuals at all roosts with a peak in the middle of the non-breeding season. Instead, we observed irregular temporal variation in roost size, suggesting that VBPs move well beyond the immediate surroundings of one roost as they track resources during the non-breeding season (see also Forshaw, 2010; Prestes et al., 2014). As a result, individuals counted at one roost in a given month may very well be present at a different roost in another month. This is why we based our WSC estimate on the month with the highest estimate of each year (February 2016 and May 2017) and not on a sum of each roost's highest monthly estimate. Uncertainty about movement is also the reason behind concentrating monthly counts in as short a period as possible. We cannot be certain that VBPs don't move further than the reported maximum daily displacement of 17 km (Prestes et al., 2014); nonetheless, our own displacement between roosts was 2.6 times faster. Only two of the ten roosts (*Ipuçu* and *São Domingos*) have two neighboring roosts within 30 km of distance, and these were always sampled on consecutive days minimizing the possibility of parrot movement between counts. Ideally, one would have different observers counting all the roosts at the same time, but barring that possibility we believe that our design is one acceptable compromise.

Two further sources of uncertainty originate within counts. These are double counting (false positive) and imperfect detection (false negative). They are more methodological in nature, but should also guide decisions of study design and data analysis for estimating population sizes. In parrot roost counts, double counting happens when observers overestimate the number of parrots in a flock, and when parrots move out of sight and are mistakenly counted as different individuals when they reappear. Our comparison of MR and HC results was an attempt to evaluate the consequences of being less or more conservative about the possibility of double counting. The consequences were negligible: 95% credible intervals of the MR and HC-based estimates for WSC

overlapped in all but one month (May 2017). In this month, the difference was 197 individuals. The tendency for higher precision in MR than HC estimates stems from a greater agreement among MR, than among HC results for the same roost and month. All else being equal, greater similarity of counts fed into an N-mixture model results in higher estimates of detection probability and therefore greater precision of the abundance estimate. This is no proof that MR counts are indeed closer to the true value, but it does support our reliance on the MR estimates. We suggest that by including MR and HC estimates in monitoring efforts for other parrots, researchers can assess the potential effects of double-counting on population estimates.

Despite all our efforts to surround the roosts, work with three-observer teams, and connect each team's observers by radio, the WSC counts taken by different teams at the same place and time still differed. This problem of imperfect detection cannot be completely eradicated, but it should be accounted for. Detection probability ( $p$ ) was always estimated to be  $>0.6$  on MR estimates, which is reassuring; however, its variation through time makes it clear that  $p$  can't be estimated once and subsequently used to correct all counts from then on. Researchers can address imperfect detection by replicating counts and estimating  $p$  during every time period for which they want to estimate  $N$ . Furthermore, the temporal variation in estimated  $p$  suggests that it is more than a simple function of observer experience. Part of the field team gained experience with the species, the sites, and the logistics over the course of the study in WSC, but  $p$  did not increase monotonically from the beginning to the end of the sampling period. Instead,  $p$  varied from month to month without any apparent trend, reaching its maximum in March 2016 and its minimum in April 2016 (Table 1). Detection at dawn was slightly (though measurably) lower than at dusk, likely due to mist forming more frequently during the morning than in the afternoon, but such intra-day variation was an order of magnitude lower than the variation between months. We conclude that failure to detect parrots at roost counts is largely a matter of chance, weather, and unpredictable parrot movements—not a matter of observer experience.

The difference between the number of parrots estimated and counted over the whole range is not just due to the failure to detect some parrots at roosts that were visited. Only 69% of known roosts were visited in 2016 and 66% in 2017. The Bayesian MCMC-based implementation of our model accounts for this incomplete coverage by imputing values of  $N$  for each roost that was not visited, in agreement with the value of  $\lambda$  estimated across roosts for the corresponding year. Multiplying the coverage of 0.66–0.69 by the average detection probability of 0.67–0.70 estimated by models 1 and 2, one obtains products of 0.45–0.47, which approximate the ratios of counted to estimated individuals in Table 2. We thus conclude that the improvement of data quality for whole-range estimates should benefit more from increasing the number of sites surveyed than from attempting to increase detection at each roost, which may be beyond our control.

Habitat loss and nest poaching have caused alarming but poorly documented declines of many Neotropical parrot populations, including VBPs (Berkunsky et al., 2017; Ribeiro et al., 2009; Wright et al., 2001). Any efforts to protect these species will benefit from improved knowledge of population size and structure. We hope that our approach to estimating population size of VBPs in WSC and beyond will motivate others to obtain replicated counts of parrot roosts for this and other species and to improve on both our survey design and analyses. In an attempt to coordinate observers and gather count information for VBPs, we set up an online count-reporting tool where users can access existing data and contribute their own. The current version is available in Portuguese at: <http://vivianezulian.azurewebsites.net>. The uncertainty surrounding regional- and whole-range population estimates, however, is still high enough to justify employing a wide variety of observation techniques in monitoring Vinaceous-breasted, and other Neotropical parrots. On one front, citizen science networks such as WikiAves, XenoCanto, and eBird can offer valuable information for mapping species ranges and reproductive areas. On the other, molecular analysis of

parrots across their range would help understand seasonal movements and the spatial structure of populations. Progress will require formal integration of different types of data into one statistical model of species distribution and abundance. Molecular data collection will require effective and safe techniques for obtaining parrot DNA without endangering the sampled individuals. Our study illustrates key sources of uncertainty about parrot abundance estimates, and how they can be addressed through monitoring protocols and statistical analysis. Critically, by addressing and estimating uncertainty, parrot monitoring efforts can move beyond minimum or average roost counts to a broader understanding of what we do and do not know about parrot numbers. On that basis, one can produce reliable assessments of population trends over time.

#### Credit author statement

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#### Declaration of competing interest

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

#### Acknowledgments

This work was only possible due to the generous dedication of 112 observers and local coordinators who counted VBPs throughout their distribution in 2016 and 2017. We thank Juarez Camara and Deizi Groth for invaluable local assistance and encouragement in WSC. *FATMA*, the *Grimpeiro* non-governmental organization, *Palmasola S/A* lumber company, *Ministerio de Ecología y RNR* (Misiones), and many local landowners facilitated permits or access to field sites or housing. We also thank IUCN for species range shapefiles. Fieldwork was supported by Aves Argentinas/AOP, the Loro Parque Foundation, and by grants from the Rufford Foundation (18013-D to KLC and 19835-1 to VZ), *Fundação Grupo Boticário de Proteção à Natureza* (to JM), Columbus Zoo & Aquarium (to KLC), and CNPq (PP 312606/2013-3, to GF).

#### Appendix A. Supplementary data

Supplementary materials to this article can be found online at <https://doi.org/10.1016/j.biocon.2020.108672>.

## References

- Abe, L.M., 2004. Caracterização do hábitat do Papagaio-de-peito-roxo *Amazona vinacea* (Kuhl, 1820) no município de Tunas do Paraná, região metropolitana de Curitiba, Paraná MSc Thesis. Universidade Federal do Paraná, Curitiba, Brazil.
- Baptista, S.R., Rudel, T.K., 2006. A re-emerging Atlantic forest? Urbanization, industrialization and the forest transition in Santa Catarina, southern Brazil. *Environ. Conserv.* 33, 195.
- Barker, R.J., Schofield, M.R., Link, W.A., Sauer, J.R., 2018. On the reliability of N-mixture models for count data. *Biometrics* 74, 369–377.
- Berkunsky, I., et al., 2017. Current threats faced by Neotropical parrot populations. *Biol. Conserv.* 214, 278–287.
- BirdLife International, 2020. The IUCN Red List of Threatened Species. Available at: <https://www.iucnredlist.org/>.
- BirdLife International, Handbook of the Birds of the World, 2016. *Amazona vinacea*. The IUCN Red List of Threatened Species. Version 2019-2. Available at: <https://www.iucnredlist.org/>.
- Bonaparte, E.B., Cockle, K.L., 2017. Nest niche overlap among the endangered Vinaceous-breasted parrot (*Amazona vinacea*) and sympatric cavity-using birds, mammals, and social insects in the subtropical Atlantic Forest, Argentina. *Condor* 119, 58–72.
- Brown, J.H., Mehlman, D.W., Stevens, G.C., 1995. Spatial variation in abundance. *Ecology* 76, 2028–2043.
- Carrara, L.A., Faria, L.C., Matos, J.R., de T.Z. Antas, P., 2008. Papagaio-de-peito-roxo *Amazona vinacea* (Kuhl) (Aves: Psittacidae) no norte do Espírito Santo: redescoberta e conservação. *Rev. Bras. Zool.* 25, 154–158.
- Casagrande, D.G., Beissinger, S.R., 1997. Evaluation of four methods for estimating parrot population size. *Condor* 99, 445–457.
- Caughley, G., 1994. Directions in conservation biology. *J. Anim. Ecol.* 63, 215.
- Caziani, S.M., Rocha Olivio, O., Rodríguez Ramírez, Eduardo, Romano, M., Derlindati, E.J., Tálamo, A., Ricalde, D., Quiroga, C., Pablo Contreras, J., Valqui, M., Sosa, H., 2007. Seasonal distribution, abundance, and nesting of Puna, Andean, and Chilean flamingos. *Condor* 109, 276.
- Cockle, K., Capuzzi, G., Bodrati, A., Clay, R., del Castillo, H., Velázquez, M., Areta, J.I., Fariña, N., Fariña, R., 2007. Distribution, abundance, and conservation of Vinaceous amazons (*Amazona vinacea*) in Argentina and Paraguay. *J. Field Ornithol.* 78, 21–39.
- Cockle, K.L., Ibarra, J.T., Altamirano, T.A., Martin, K., 2019. Interspecific networks of cavity-nesting vertebrates reveal a critical role of broadleaf trees in endangered *Araucaria* mixed forests of South America. *Biodivers. Conserv.* 28, 3371–3386.
- Collar, N., Gonzaga, L.P., Krabbe, N., Madrono Nieto, A., Naranjo, L.G., Parker, T.A., Wege, D.C., 1992. Threatened Birds of the Americas: The ICBP/IUCN Red Data Book, 3rd ed. International Council for Bird Preservation, Cambridge, UK.
- Collar, N., Boesman, P., Juana, E., 2017. Vinaceous-breasted Amazon (*Amazona vinacea*). In: Handbook of the Birds of the World Alive. Lynx Edicions, Barcelona.
- Conn, P.B., Johnson, D.S., Williams, P.J., Melin, S.R., Hooten, M.B., 2018. A guide to Bayesian model checking for ecologists. *Ecol. Monogr.* 88, 526–542.
- Cooch, E., White, G., 2020. Program MARK: 'A Gentle Introduction' Available at: <http://www.phidot.org/software/mark/docs/book>.
- Cougill, S., Marsden, S.J., 2004. Variability in roost size in an Amazona parrot: implications for roost monitoring. *J. Field Ornithol.* 75, 67–73.
- Dénes, F.V., Tella, J.L., Beissinger, S.R., 2018. Revisiting methods for estimating parrot abundance and population size. *Emu* 118, 67–79.
- Dorazio, R.M., Martin, J., Edwards, H.H., 2013. Estimating abundance while accounting for rarity, correlated behavior, and other sources of variation in counts. *Ecology* 94, 1472–1478.
- Fearnside, P.M., 2001. Soybean cultivation as a threat to the environment in Brazil. *Environ. Conserv.* 28, 23–38.
- Forshaw, J.M., 2010. Parrots of the world. In: Princeton Field Guides. Princeton University Press, Princeton.
- Gaston, K.J., 1994. Rarity. Chapman & Hall, London.
- Gaston, K.J., 2009. Geographic range limits: achieving synthesis. *Proc. R. Soc. B Biol. Sci.* 276, 1395–1406.
- Gelman, A., Meng, X.L., Stern, H.S., 1996. Posterior predictive assessment of model fitness via realized discrepancies (with discussion). *Stat. Sin.* 6, 733–807.
- Hasenack, H., da Silva, J.S., Weber, E.J., Hofmann, G.S., 2017. A digital version of Hueck's vegetation map of South America: 50 years after the release of his book on the sub-continent's forests. *Geografía y Sistemas de Información Geográfica (GEOSIG)* 9, 11–15.
- Hueck, K., 1966. Die Wälder Südamerikas. In: *Ökologie, Zusammensetzung und wirtschaftliche Bedeutung*. Verlag, Stuttgart.
- IBGE, 2015. Divisão Territorial Brasileira. Available at: <https://www.ibge.gov.br/>.
- Kéry, M., Royle, J.A., 2016. Applied Hierarchical Modeling in Ecology: Analysis of Distribution, Abundance and Species Richness in R and BUGS: Volume 1: Prelude and Static Models. Academic Press.
- Lawton, J.H., 1995. Population dynamic principles. In: *Extinction Rates*. Oxford University Press, Oxford, pp. 147–163.
- Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D., 2000. WinBUGS—a Bayesian modelling framework: concepts, structure, and extensibility. *Stat. Comput.* 10, 325–337.
- Mace, G.M., Collar, N.J., Gaston, K.J., Hilton-Taylor, C., Akçakaya, H.R., Leader-Williams, N., Milner-Gulland, E.J., Stuart, S.N., 2008. Quantification of extinction risk: IUCN's system for classifying threatened species. *Conserv. Biol.* 22, 1424–1442.
- Mantovani, A., Morellato, L.P.C., dos Reis, M., 2004. Fenologia reprodutiva e produção de sementes em *Araucaria angustifolia* (Bert.) O. Kuntze. *Rev. Bras. Bot.* 27, 787–796.
- Marsden, S.J., Royle, K., 2015. Abundance and abundance change in the world's parrots. *Ibis* 157, 219–229.
- Martin, J., Royle, J.A., Mackenzie, D.I., Edwards, H.H., Kéry, M., Gardner, B., 2011. Accounting for non-independent detection when estimating abundance of organisms with a Bayesian approach: correlated behaviour and abundance. *Methods Ecol. Evol.* 2, 595–601.
- Matuzak, G.D., Brightsmith, D.J., 2007. Roosting of yellow-naped parrots in Costa Rica: estimating the size and recruitment of threatened populations. *J. Field Ornithol.* 78, 159–169.
- MMA, 2007. Mapa de Cobertura Vegetal dos Biomas Brasileiros. Available at: <https://www.mma.gov.br/component/k2/item/7626-mapas-de-cobertura-vegetal.html>.
- Mohd-Azlan, J., Zubaid, A., Kunz, T.H., 2001. Distribution, relative abundance, and conservation status of the large flying fox, *Pteropus vampyrus*, in peninsular Malaysia: a preliminary assessment. *Acta Chiropterologica* 3, 149–162.
- Norris, K.E.N., 2004. Managing threatened species: the ecological toolbox, evolutionary theory and declining-population paradigm. *J. Appl. Ecol.* 41, 413–426.
- Olah, G., Butchart, S.H.M., Symes, A., Guzmán, I.M., Cunningham, R., Brightsmith, D.J., Heinsohn, R., 2016. Ecological and socio-economic factors affecting extinction risk in parrots. *Biodivers. Conserv.* 25, 205–223.
- Olson, D.M., Dinerstein, E., Wikramanayake, E.D., Burgess, N.D., Powell, G.V., Underwood, E.C., D'Amico, J.A., Itoua, I., Strand, H.E., Morrison, J.C., 2001. Terrestrial ecoregions of the world: a new map of life on earth: a new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. *BioScience* 51, 933–938.
- Plummer, M., 2003. JAGS: a program for analysis of Bayesian graphical models using Gibbs sampling. In: *Proceedings of the 3rd International Workshop on Distributed Statistical Computing*. Vienna, pp. 125.
- Prestes, N.P., Martinez, J., Kilpp, J.C., Batistela, T., Turkievicz, A., Rezende, É., Gaboardi, V.T.R., 2014. Ecologia e conservação de *Amazona vinacea* em áreas simpátricas com *Amazona pretrei*. *Ornithologia* 6, 109–120.
- Renton, K., Salinas-Melgoza, A., De Labra-Hernández, M.A., de la Parra-Martínez, S.M., 2015. Resource requirements of parrots: nest site selectivity and dietary plasticity of Psittaciformes. *J. Ornithol.* 156, S73–S90.
- Ribeiro, M.C., Metzger, J.P., Martensen, A.C., Ponzoni, F.J., Hirota, M.M., 2009. The Brazilian Atlantic Forest: how much is left, and how is the remaining forest distributed? Implications for conservation. *Biol. Conserv.* 142, 1141–1153.
- Royle, J.A., 2004. N-mixture models for estimating population size from spatially replicated counts. *Biometrics* 60, 108–115.
- Segovia, J.M., Cockle, K.L., 2012. Conservación del Loro vinoso (*Amazona vinacea*) en Argentina. *El hornero* 27, 027–037.
- Tella, J.L., Dénes, F.V., Zulian, V., Prestes, N.P., Martínez, J., Blanco, G., Hiraldo, F., 2016. Endangered plant-parrot mutualisms: seed tolerance to predation makes parrots pervasive dispersers of the Parana pine. *Sci. Rep.* 6, 31709.
- Walsh, A.L., Harris, S., 1996. Factors determining the abundance of Vespertilionid bats in Britain: geographical, land class and local habitat relationships. *J. Appl. Ecol.* 33, 519–529.
- Webb, M.H., Wotherspoon, S., Stojanovic, D., Heinsohn, R., Cunningham, R., Bell, P., Terauds, A., 2014. Location matters: using spatially explicit occupancy models to predict the distribution of the highly mobile, endangered swift parrot. *Biol. Conserv.* 176, 99–108.
- Wikiaves, 2018. Papagaio-de-peito-roxo. Available at: <https://www.wikiaves.com.br/wiki/papagaio-de-peito-roxo>.
- Wright, T.F., et al., 2001. Nest poaching in neotropical parrots. *Conserv. Biol.* 15, 710–720.

**Supplemental Material Table S1.** Whole-range count sites by country and region, with contact observer, and the year sampled. Contacts given with initials are co-authors of this paper.

| Country and Region | Site                          | Contact                  | Year Sampled |      |
|--------------------|-------------------------------|--------------------------|--------------|------|
|                    |                               |                          | 2016         | 2017 |
| <b>ARGENTINA</b>   |                               |                          |              |      |
| Misiones           | 1. San Pedro – Centro         | KC* and Bianca Bonaparte | X            |      |
|                    | 2. San Pedro – Siete Estellas | KC and Bianca Bonaparte  | X            |      |
|                    | 3. Cruce Caballero            | KC and Bianca Bonaparte  | X            |      |
|                    | 4. Alegría                    | KC and Bianca Bonaparte  | X            |      |
|                    | 5. Tobuna                     | KC and Bianca Bonaparte  | X            |      |
|                    | 6. Santa Rosa                 | KC and Bianca Bonaparte  | X            |      |
|                    | 7. Irigoyen                   | KC and Bianca Bonaparte  | X            |      |
| <b>BRAZIL</b>      |                               |                          |              |      |
| Espírito Santo     | 8. Dores do Rio Preto         | Tatiane Pongiluppi       |              | X    |
| Minas Gerais       | 9. Minas Gerais               | Sérgio Carvalho          | X            |      |
|                    | 10. Carrancas e Minduri       | Kassius Santos           | X            | X    |
|                    | 11. Baipendi                  | Emanuel Ladroz           | X            |      |
|                    | 12. Santo Antônio do Grama    | Leonardo Miranda         | X            |      |
|                    | 13. Luminárias                | Kassius Santos           | X            |      |
|                    | 14. Serra do Cipó             | Lucas Carrara            |              | X    |
|                    | 15. Crisólita                 | Marina Somenzari         |              | X    |
| Paraná             | 16. General Carneiro A        | NPP†, JM§ and RTJr¶      | X            | X    |
|                    | 17. General Carneiro B        | NPP, JM and RTJr         | X            |      |
|                    | 18. General Carneiro C        | NPP, JM and RTJr         |              | X    |
|                    | 19. General Carneiro D        | NPP, JM and RTJr         |              | X    |
|                    | 20. General Carneiro E        | NPP, JM and RTJr         |              | X    |
|                    | 21. Bituruna                  | NPP, JM and RTJr         |              | X    |
|                    | 22. Curitiba A                | Roberto Boçon            | X            |      |
|                    | 23. Curitiba B                | Romulo da Silva          | X            |      |
|                    | 24. Curitiba C                | Rafael Sezerban          | X            |      |
|                    | 25. Curitiba D                | Roberto Boçon            |              | X    |
|                    | 26. Curitiba E                | Roberto Boçon            |              | X    |
|                    | 27. Curitiba F                | Rafael Sezerban          |              | X    |

**Supplemental Material Table S1: (cont.)**

| Country and Region | Site                                | Contact            | Year Sampled |      |
|--------------------|-------------------------------------|--------------------|--------------|------|
|                    |                                     |                    | 2016         | 2017 |
|                    | 28. Bocaiúva do Sul A               | Elenise Sipinski   | X            | X    |
|                    | 29. Bocaiúva do Sul B               | Romulo da Silva    | X            |      |
|                    | 30. Tunas do Paraná                 | Roberta Boss       | X            |      |
|                    | 31. Bocaiúva do Sul/Tunas do PR     | Pedro Scherer-Neto |              | X    |
|                    | 32. Bocaiúva do Sul C               | Patricia Serafini  | X            |      |
|                    | 33. Castro/Pirai do Sul/Jaguariaíva | Tony Teixeira      |              | X    |
|                    | 34. Jaguariaíva                     | Tony A. Bichinky   | X            |      |
|                    | 35. Tibagi A                        | Romulo da Silva    | X            |      |
|                    | 36. Tibagi B                        | Romulo da Silva    | X            |      |
|                    | 37. Coronel Domingos Soares         | NPP, JM and RTJr   |              | X    |
|                    | 38. Inácio Martins                  | NPP, JM and RTJr   | X            | X    |
|                    | 39. Palmas                          | NPP, JM and RTJr   | X            | X    |
|                    | 40. Pinhão                          | NPP, JM and RTJr   | X            | X    |
|                    | 41. Telêmaco Borba                  | Roberto Boçon      | X            | X    |
|                    | 42. União da Vitória                | NPP, JM and RTJr   |              | X    |
| Rio Grande do Sul  | 43. Barracão                        | NPP, JM and RTJr   | X            | X    |
|                    | 44. Sarandi                         | NPP, JM and RTJr   | X            | X    |
|                    | 45. Coqueiros do Sul                | NPP, JM and RTJr   |              | X    |
|                    | 46. Canela                          | NPP, JM and RTJr   | X            | X    |
|                    | 47. Bom Jesus                       | NPP, JM and RTJr   | X            | X    |
|                    | 48. Bom Jesus B                     | NPP, JM and RTJr   | X            | X    |
|                    | 49. São José dos Ausentes           | NPP, JM and RTJr   | X            | X    |
|                    | 50. Miraguaí                        | NPP, JM and RTJr   |              | X    |
|                    | 51. Dois Irmãos da Missão           | NPP, JM and RTJr   |              | X    |
| Santa Catarina     | 52. Cerro Negro                     | NPP, JM and RTJr   | X            | X    |
|                    | 53. Abdon Batista                   | NPP, JM and RTJr   |              | X    |
|                    | 54. Abelardo Luz                    | VZ** and ESM††     | X            | X    |
|                    | 55. Passos Maia                     | Vanessa Kanaan     |              | X    |
|                    | 56. Ponte Serrada                   | Vanessa Kanaan     |              | X    |

**Supplemental Material Table S1: (cont.)**

| Country and Region | Site                  | Contact                 | Year Sampled |      |
|--------------------|-----------------------|-------------------------|--------------|------|
|                    |                       |                         | 2016         | 2017 |
|                    | 57. Água Doce         | VZ and ESM              | X            | X    |
|                    | 58. Anitápolis        | NPP, JM and RTJr        | X            |      |
|                    | 59. Anitápolis B      | NPP, JM and RTJr        | X            |      |
|                    | 60. Bom Retiro        | NPP, JM and RTJr        | X            |      |
|                    | 61. Campo Belo do Sul | NPP, JM and RTJr        | X            | X    |
|                    | 62. Campo Erê         | VZ and ESM              | X            | X    |
|                    | 63. Ipuaçú            | VZ and ESM              |              | X    |
|                    | 64. Entre Rios        | VZ and ESM              | X            | X    |
|                    | 65. Guatambu          | VZ and ESM              | X            | X    |
|                    | 66. Irineópolis       | NPP, JM and RTJr        | X            | X    |
|                    | 67. Itaiópolis        | NPP, JM and RTJr        | X            |      |
|                    | 68. Lebon Régis       | NPP, JM and RTJr        | X            | X    |
|                    | 69. Lebon Régis B     | NPP, JM and RTJr        | X            | X    |
|                    | 70. Lebon Régis C     | NPP, JM and RTJr        | X            |      |
|                    | 71. Lebon Régis D     | NPP, JM and RTJr        | X            |      |
|                    | 72. Lebon Régis E     | NPP, JM and RTJr        | X            |      |
|                    | 73. Lebon Régis F     | NPP, JM and RTJr        |              | X    |
|                    | 74. Lebon Régis G     | NPP, JM and RTJr        |              | X    |
|                    | 75. Lebon Régis H     | NPP, JM and RTJr        |              | X    |
|                    | 76. Lebon Régis I     | NPP, JM and RTJr        |              | X    |
|                    | 77. Lorentino         | Miguel Angelo Biz       | X            |      |
|                    | 78. Palma Sola        | Paulo A. Neto, VZ e ESM | X            | X    |
|                    | 79. Urupema           | NPP, JM and RTJr        | X            | X    |
|                    | 80. Urupema           | NPP, JM and RTJr        | X            | X    |
|                    | 81. Painei            | NPP, JM and RTJr        | X            | X    |
|                    | 82. São Joaquim       | NPP, JM and RTJr        | X            | X    |
|                    | 83. São Joaquim       | NPP, JM and RTJr        | X            | X    |
|                    | 84. Painei            | NPP, JM and RTJr        | X            | X    |
|                    | 85. Quilombo          | VZ and ESM              |              | X    |
|                    | 86. Santa Cecília A   | NPP, JM and RTJr        |              | X    |

**Supplemental Material Table S1: (cont.)**

| Country and Region | Site                            | Contact             | Year Sampled |      |
|--------------------|---------------------------------|---------------------|--------------|------|
|                    |                                 |                     | 2016         | 2017 |
|                    | 87 Santa Cecília B              | NPP, JM and RTJr    |              | X    |
|                    | 88. Santa Cecília C             | NPP, JM and RTJr    |              | X    |
|                    | 89. São Domingos                | VZ and ESM          | X            | X    |
|                    | 90. Urubici                     | NPP, JM and RTJr    | X            |      |
|                    | 91. Porto União                 | NPP, JM and RTJr    |              | X    |
|                    | 92. Urubici                     | NPP, JM and RTJr    | X            |      |
| São Paulo          | 93. Timburi                     | Fernando Zurdo      | X            |      |
|                    | 94. São Paulo                   | Fernando Zurdo      | X            | X    |
|                    | 95. Campos do Jordão            | Luís Fábio Silveira | X            | X    |
| PARAGUAY           |                                 |                     |              |      |
| Canindeyú          | 96. Refúgio Biológico Carapá    | AL§§                | X            | X    |
|                    | 97. Reserva Privada Itabó Rivas | AL                  | X            |      |
| Alto Paraná        | 98. Reserva Biológica de Limoy  | AL                  | X            | X    |

\* KC = Kristina L. Cockle

† NPP = Nêmora Pauletti Prestes

§ JM = Jaime Martinez

¶ RTJr = Roberto Tomasi Júnior

\*\* VZ = Viviane Zulian

†† ESM = Eliara Solange Müller

§§ AL = Arne Lesterhuis

**Supplemental Material Table S2.** Monthly counts and estimates  $\pm$  standard deviation of the local abundance for each WSC (regional-scale) roost throughout the study period, based on ‘highly conservative’ (HC) and ‘most reasonable’ (MR) count results. Numbers in parentheses show the highest count for the corresponding roost and month. Roosts with NA in parentheses do not have counts in the corresponding month; their estimates for those months are derived from Model 1. Roost order in the table is longitudinal from West to East.

| Year | Month\Roost | Palma Sola      | Campo Erê          | Guatambu          | Quilombo           | São Domingos      |                   |
|------|-------------|-----------------|--------------------|-------------------|--------------------|-------------------|-------------------|
| 2016 | December    | (MR)            | 12 $\pm$ 4 (10)    | 71 $\pm$ 24 (NA)  | 165 $\pm$ 10 (155) | 71 $\pm$ 23 (NA)  | 83 $\pm$ 8 (75)   |
|      |             | (HC)            | 13 $\pm$ 6 (8)     | 69 $\pm$ 24 (NA)  | 157 $\pm$ 13 (143) | 69 $\pm$ 24 (NA)  | 81 $\pm$ 10 (71)  |
|      | January     | (MR)            | 86 $\pm$ 18 (65)   | 110 $\pm$ 14 (NA) | 221 $\pm$ 26 (175) | 109 $\pm$ 32 (NA) | 27 $\pm$ 13 (10)  |
|      |             | (HC)            | 72 $\pm$ 17 (53)   | 96 $\pm$ 31 (NA)  | 192 $\pm$ 25 (158) | 96 $\pm$ 31 (NA)  | 25 $\pm$ 14 (10)  |
|      | February    | (MR)            | 129 $\pm$ 19 (101) | 182 $\pm$ 41 (NA) | 191 $\pm$ 26 (141) | 183 $\pm$ 41 (NA) | 100 $\pm$ 17 (77) |
|      |             | (HC)            | 126 $\pm$ 21 (94)  | 182 $\pm$ 46 (NA) | 192 $\pm$ 30 (137) | 182 $\pm$ 45 (NA) | 102 $\pm$ 19 (75) |
|      | March       | (MR)            | 76 $\pm$ 7 (68)    | 136 $\pm$ 31 (NA) | 61 $\pm$ 7 (51)    | 136 $\pm$ 31 (NA) | 32 $\pm$ 6 (25)   |
|      |             | (HC)            | 67 $\pm$ 5 (63)    | 123 $\pm$ 30 (NA) | 51 $\pm$ 5 (47)    | 123 $\pm$ 31 (NA) | 27 $\pm$ 5 (24)   |
|      | April       | (MR)            | 32 $\pm$ 15 (5)    | 148 $\pm$ 35 (NA) | 246 $\pm$ 22 (197) | 148 $\pm$ 35 (NA) | 59 $\pm$ 11 (39)  |
|      |             | (HC)            | 43 $\pm$ 21 (5)    | 154 $\pm$ 39 (NA) | 255 $\pm$ 29 (191) | 155 $\pm$ 39 (NA) | 65 $\pm$ 14 (35)  |
|      | May         | (MR)            | 48 $\pm$ 16 (25)   | 47 $\pm$ 16 (25)  | 63 $\pm$ 15 (40)   | 152 $\pm$ 35 (NA) | 83 $\pm$ 18 (58)  |
|      |             | (HC)            | 72 $\pm$ 34 (21)   | 74 $\pm$ 35 (24)  | 81 $\pm$ 30 (36)   | 175 $\pm$ 48 (NA) | 96 $\pm$ 36 (45)  |
|      | June        | (MR)            | 6 $\pm$ 6 (0)      | 4 $\pm$ 4 (0)     | 40 $\pm$ 7 (29)    | 139 $\pm$ 31 (NA) | 35 $\pm$ 8 (24)   |
|      |             | (HC)            | 6 $\pm$ 6 (0)      | 4 $\pm$ 4 (0)     | 37 $\pm$ 8 (26)    | 132 $\pm$ 31 (NA) | 33 $\pm$ 8 (22)   |
| July | (MR)        | 38 $\pm$ 8 (31) | 55 $\pm$ 9 (46)    | 18 $\pm$ 7 (12)   | 65 $\pm$ 23 (NA)   | 58 $\pm$ 10 (45)  |                   |
|      | (HC)        | 35 $\pm$ 7 (30) | 44 $\pm$ 8 (37)    | 13 $\pm$ 6 (8)    | 58 $\pm$ 22 (NA)   | 54 $\pm$ 11 (42)  |                   |
| 2017 | February    | (MR)            | 173 $\pm$ 15 (131) | 23 $\pm$ 5 (17)   | 200 $\pm$ 12 (184) | 89 $\pm$ 25 (NA)  | 51 $\pm$ 10 (32)  |
|      |             | (HC)            | 151 $\pm$ 14 (124) | 21 $\pm$ 4 (17)   | 164 $\pm$ 12 (150) | 75 $\pm$ 25 (NA)  | 38 $\pm$ 8 (25)   |
|      | March       | (MR)            | 202 $\pm$ 17 (177) | 27 $\pm$ 8 (18)   | 152 $\pm$ 15 (125) | 115 $\pm$ 29 (NA) | 67 $\pm$ 11 (54)  |
|      |             | (HC)            | 193 $\pm$ 22 (162) | 36 $\pm$ 15 (18)  | 163 $\pm$ 23 (118) | 118 $\pm$ 33 (NA) | 63 $\pm$ 17 (41)  |
|      | April       | (MR)            | 154 $\pm$ 13 (135) | 29 $\pm$ 5 (23)   | 178 $\pm$ 15 (157) | 94 $\pm$ 26 (NA)  | 44 $\pm$ 9 (35)   |
|      |             | (HC)            | 145 $\pm$ 16 (126) | 31 $\pm$ 8 (22)   | 137 $\pm$ 19 (113) | 86 $\pm$ 27 (NA)  | 40 $\pm$ 13 (23)  |
|      | May         | (MR)            | 49 $\pm$ 11 (34)   | 34 $\pm$ 10 (20)  | 183 $\pm$ 17 (147) | 38 $\pm$ 10 (25)  | 42 $\pm$ 11 (27)  |
|      |             | (HC)            | 42 $\pm$ 8 (34)    | 27 $\pm$ 8 (20)   | 153 $\pm$ 12 (135) | 26 $\pm$ 7 (19)   | 30 $\pm$ 8 (22)   |
|      | June        | (MR)            | 121 $\pm$ 17 (84)  | 40 $\pm$ 18 (5)   | 117 $\pm$ 16 (84)  | 33 $\pm$ 12 (12)  | 76 $\pm$ 15 (45)  |
|      |             | (HC)            | 110 $\pm$ 19 (81)  | 49 $\pm$ 23 (5)   | 122 $\pm$ 22 (77)  | 35 $\pm$ 17 (8)   | 82 $\pm$ 20 (41)  |



**Supplemental Material Table S2. (cont.)**

| Year | Month\Roost | Ipaçu      | Entre Rios   | Abelardo Luz | Água Doce    | Lebon Régis  |              |
|------|-------------|------------|--------------|--------------|--------------|--------------|--------------|
| 2016 | December    | (MR)       | 72±23 (NA)   | 71±23 (NA)   | 71±22 (NA)   | 26±2 (25)    | 71±23 (NA)   |
|      |             | (HC)       | 69±24 (NA)   | 68±24 (NA)   | 68±24 (NA)   | 25±4 (22)    | 68±24 (NA)   |
|      | January     | (MR)       | 109±32 (NA)  | 109±32 (NA)  | 110±33 (NA)  | 103±17 (85)  | 109±32 (NA)  |
|      |             | (HC)       | 95±32 (NA)   | 96±32 (NA)   | 96±31 (NA)   | 94±17 (76)   | 96±32 (NA)   |
|      | February    | (MR)       | 183±41 (NA)  | 182±41 (NA)  | 129±27 (77)  | 366±34 (300) | 182±41 (NA)  |
|      |             | (HC)       | 183±44 (NA)  | 182±44 (NA)  | 134±31 (77)  | 360±38 (287) | 182±44 (NA)  |
|      | March       | (MR)       | 136±30 (NA)  | 136±30 (NA)  | 19±5 (14)    | 495±12 (481) | 136±30 (NA)  |
|      |             | (HC)       | 123±31 (NA)  | 123±32 (NA)  | 17±4 (14)    | 453±11 (440) | 123±31 (NA)  |
|      | April       | (MR)       | 148±35 (NA)  | 148±35 (NA)  | 82±17 (48)   | 323±25 (273) | 148±35 (NA)  |
|      |             | (HC)       | 155±39 (NA)  | 154±39 (NA)  | 86±23 (42)   | 325±30 (265) | 154±40 (NA)  |
|      | May         | (MR)       | 152±35 (NA)  | 44±22 (8)    | 140±19 (114) | 215±24 (184) | 579±22 (543) |
|      |             | (HC)       | 175±47 (NA)  | 75±39 (8)    | 164±38 (110) | 233±44 (178) | 610±40 (543) |
|      | June        | (MR)       | 139±31 (NA)  | 140±31 (NA)  | 450±12 (433) | 304±12 (275) | 140±30 (NA)  |
|      |             | (HC)       | 133±32 (NA)  | 133±31 (NA)  | 430±13 (409) | 287±12 (267) | 133±31 (NA)  |
| July | (MR)        | 66±22 (NA) | 65±23 (NA)   | 166±16 (143) | 58±11 (44)   | 65±23 (NA)   |              |
|      | (HC)        | 58±22 (NA) | 58±22 (NA)   | 155±16 (131) | 49±10 (38)   | 58±22 (NA)   |              |
| 2017 | February    | (MR)       | 89±25 (NA)   | 89±25 (NA)   | 62±9 (42)    | 28±6 (20)    | 89±25 (NA)   |
|      |             | (HC)       | 75±25 (NA)   | 76±24 (NA)   | 57±9 (42)    | 22±5 (16)    | 75±24 (NA)   |
|      | March       | (MR)       | 115±30 (NA)  | 115±29 (NA)  | 202±17 (174) | 46±8 (39)    | 115±29 (NA)  |
|      |             | (HC)       | 117±33 (NA)  | 117±34 (NA)  | 198±24 (155) | 53±15 (35)   | 118±34 (NA)  |
|      | April       | (MR)       | 94±26 (NA)   | 94±25 (NA)   | 133±11 (122) | 27±7 (21)    | 94±26 (NA)   |
|      |             | (HC)       | 86±28 (NA)   | 86±27 (NA)   | 134±16 (115) | 29±11 (19)   | 86±28 (NA)   |
|      | May         | (MR)       | 328±19 (289) | 44±19 (6)    | 264±15 (242) | 169±17 (132) | 744±19 (705) |
|      |             | (HC)       | 304±15 (280) | 30±15 (6)    | 207±12 (193) | 146±13 (122) | 729±15 (705) |
|      | June        | (MR)       | 15±11 (2)    | 109±29 (NA)  | 349±18 (320) | 122±18 (87)  | 109±29 (NA)  |
|      |             | (HC)       | 21±16 (0)    | 110±32 (NA)  | 336±24 (295) | 125±23 (81)  | 110±32 (NA)  |

**Supplemental Material Appendix A:** BUGS language specification of the models used in estimating Vinaceous-breasted Parrot abundance. Model A is the model used for the regional scale analysis of Western Santa Catarina data. Models B and C correspond to Model 1 and Model 2, respectively, in the text; they were used for analyzing data at the whole-range scale. All models were based on Royle (2004) and Kéry and Royle (2016).

```
#Model A: Regional analysis with WSC data

#Data object
str(bdata <- list(counts = counts, month = month, site = site, n =
nrow(counts), visit = ncol(counts), nmonth = max(month), morning = COV2-
1))

# Specify model in BUGS language
cat(file = "modelA.txt", "
model {

# Priors
# for abundance
for(s in 1:nmonth){
  lambda[s] ~ dgamma(0.01, 0.01)
  beta0[s] ~ dunif(-10,10)
}
# for detection
beta1 ~ dunif(-10,10)

# Biological model for true abundance
for(i in 1:n){ # loop over sites
  N[i] ~ dpois(lambda[month[i]])
  # Observed data at replicated counts
  for(j in 1:visit){ #loop over visits in each site
    counts[i,j] ~ dbin(p[i,j], N[i])
    logit(p[i,j]) <- beta0[month[i]] + beta1*morning[i,j]

    ## Commands for computing Bayesian p-value
    eval[i,j] <- p[i,j]*N[i]
    E[i,j] <- pow((counts[i,j] - eval[i,j]),2) / (eval[i,j] + 0.5)
    # Generate replicate data and compute fit stats
    C.new[i,j] ~ dbin(p[i,j], N[i])
    E.new[i,j] <- pow((C.new[i,j] - eval[i,j]),2)/(eval[i,j]+0.5)
  } #counts
} #sites

fit <- sum(E)
fit.new <- sum(E.new)
c.hat <- fit / fit.new
# Total abundance across all sites
Ntotal[1] <- sum(N[1:10])
Ntotal[2] <- sum(N[11:20])
Ntotal[3] <- sum(N[21:30])
Ntotal[4] <- sum(N[31:40])
Ntotal[5] <- sum(N[41:50])
Ntotal[6] <- sum(N[51:60])
Ntotal[7] <- sum(N[61:70])
Ntotal[8] <- sum(N[71:80])
Ntotal[9] <- sum(N[81:90])
```

```

    Ntotal[10] <- sum(N[91:100])
    Ntotal[11] <- sum(N[101:110])
    Ntotal[12] <- sum(N[111:120])
    Ntotal[13] <- sum(N[121:130])
  }
  ")

# Initial Values
Nst <- apply(counts, 1, max, na.rm=TRUE) + 1
Nst[Nst == '-Inf'] <- 1
inits <- function(){list(N=Nst)}

##Params monitored
params <- c('lambda', 'p', 'N', "beta0", "beta1", "fit", "fit.new",
" c.hat", "Ntotal")

# MCMC settings
na <- 1000;  nc <- 3;   nb <- 10000;   ni <- 25000;   nt <- 20

# Call JAGS
fmA <- jags(bdata, inits, params, "modelA.txt", n.adapt = na, n.chains =
nc, n.thin = nt, n.iter = ni, n.burnin = nb, parallel = TRUE)

```

```

#Model B: Whole-range analysis without covariates (Model 1 in manuscript)

#Data object
str(bdata <- list(counts = countsWR, month = monthWR, site = siteWR, n =
nrow(countsWR), visit = ncol(countsWR), nmonth = max(monthWR)))

#Specify model in BUGS language
cat(file = "modelB.txt", "
model {

  # Priors
  # for abundance
  for(s in 1:nmonth){
    lambda[s] ~ dgamma(0.01, 0.01)
  }
  # for detection
  p ~ dunif(0,1) #fixed for all sites and months

  # Biological model for true abundance
  for(i in 1:n){ # loop over sites
    N[i] ~ dpois(lambda[month[i]])
    # Observed data at replicated counts
    for(j in 1:visit){ #loop over visits in each site
      counts[i,j] ~ dbin(p, N[i])
      ## Commands for computing Bayesian p-value
      eval[i,j] <- p*N[i]
      E[i,j] <- pow((counts[i,j]-eval[i,j]),2) / (eval[i,j] + 0.5)
      # Generate replicate data and compute fit stats
      C.new[i,j] ~ dbin(p, N[i])
      E.new[i,j] <- pow((C.new[i,j] - eval[i,j]),2)/(eval[i,j]+0.5)
    } # reps
  } # sites

  fit <- sum(E)
  fit.new <- sum(E.new)
  c.hat <- fit / fit.new
  # Total abundance across all sites
  Ntotal[1] <- sum(N[1:98])
  Ntotal[2] <- sum(N[99:196])

}
")

# Initial Values
Nst <- apply(countsWR, 1, max, na.rm=TRUE) + 1
Nst[Nst == '-Inf'] <- 1
inits <- function(){list(N=Nst)}

# Parameters monitored
params <- c('lambda', 'p', 'N', 'fit', 'fit.new', 'c.hat', 'Ntotal')

# MCMC settings
na <- 1000; nc <- 3; nb <- 10000; ni <- 25000; nt <- 20

# Call JAGS
fmB <- jags(bdata, inits, params, "modelB.txt", n.adapt = na, n.chains =
nc, n.thin = nt, n.iter = ni, n.burnin = nb, parallel = TRUE)

```

```

#Model C: Whole-range analysis with covariate on abundance(Model 2 in ms)

#Data object
str(bdata <- list(counts = countsWR, month = monthWR, site = siteWR, n =
nrow(countsWR), visit = ncol(countsWR), nmonth = max(monthWR), arauc =
rep(siteCovsWR[,5],2)))

# Specify model in BUGS language
cat(file = "modelC.txt", "
model {
  # Priors
  # for abundance
  for(s in 1:nmonth){
    beta0[s] ~ dunif(-10,10)
    betal[s] ~ dunif(-10,10)
  }
  p ~ dunif(0,1) #fixed p between sites and visits of the same month

  # Biological model for true abundance
  for(i in 1:n){ #loop over sites
    N[i] ~ dpois(lambda[i])
    log(lambda[i]) <- beta0[month[i]] + betal[month[i]]*arauc[i]
    #Observed data at replicated counts
    for(j in 1:visit){ #loop over visits in each site
      counts[i,j] ~ dbin(p, N[i])
      eval[i,j] <- p*N[i]
      E[i,j] <- pow((counts[i,j]-eval[i,j]),2) / (eval[i,j] + 0.5)
      # Generate replicate data and compute fit stats
      C.new[i,j] ~ dbin(p,N[i])
      E.new[i,j] <- pow((C.new[i,j] - eval[i,j]),2)/(eval[i,j]+0.5)
    } #reps

  } #sites

  fit <- sum(E)
  fit.new <- sum(E.new)
  c.hat <- fit / fit.new
  # Total abundance across all sites
  Ntotal[1] <- sum(N[1:98])
  Ntotal[2] <- sum(N[99:196])
}
")

#Initial Values
Nst <- apply(countsWR, 1, max, na.rm=TRUE) + 1
Nst[Nst == '-Inf'] <- 1
inits <- function(){list(N=Nst)}

#Parameters monitored
params <- c('lambda', 'p', 'N', 'beta0', 'betal', 'fit', 'fit.new',
'c.hat', 'Ntotal')

#MCMC settings
na <- 1000; nc <- 3; nb <- 10000; ni <- 25000; nt <- 20

#Call JAGS
fmC <- jags(bdata, inits, params, "modelC.txt", n.adapt = na, n.chains =
nc, n.thin = nt, n.iter = ni, n.burnin = nb, parallel = TRUE)

```

**Supplemental Material Appendix B:** Simulation assessment of (1) the coverage of the posterior-stretching procedure, and (2) the choice of an overdispersion-naïve binomial N-mixture model over a  $p$ -ignorant approach

We conducted a simple simulation with two goals:

- (1) To assess the coverage of credible intervals that are computed from a 'stretched' posterior distribution as described in the main text of the article. By 'coverage' we mean the extent to which estimation credible intervals cover the true values of parameters fed to the simulation.
- (2) To assess the estimation error associated with our use of an overdispersion-naïve binomial N-mixture model and compare it with a  $p$ -ignorant method that simply adds maximum counts across sites.

For this, we simulated 1000 data sets that contained heavy overdispersion in both abundance and detection. Sample sizes were 130 sites and 2 replicate counts, with average abundance of 120 and average detection 0.7; these resembled the constraints and estimates of our whole-range analysis. Then, we analyzed each simulated data set with a simple binomial N-mixture model that had only an intercept for abundance and another one for detection. Thus, this model was overdispersion-naïve in the sense that it did not take overdispersion into account by trying to estimate it. At the same time, for each data set, we took the maximum count simulated at each site and added this up across sites for a  $p$ -ignorant estimate of  $N_{total}$ , the total abundance across all 130 sites.

We simulated the overdispersed replicated count data sets using function `simNm` in the AHMbook R package (Kéry, Royle & Meredith 2020). In this function, overdispersion can be simulated by adding Gaussian noise at the site level into the linear predictor for the log-linear model of abundance, or at the site, occasion, or site-by-occasion (= 'survey') level into the linear predictor for the logit-linear model of detection. The magnitude of each component of overdispersion is governed by the value of the standard deviation of a zero-mean Normal distribution from which the respective contributions are drawn as random numbers.

In both our regional and whole-range counts, we hypothesize that overdispersion may be present at the site-level in abundance and at the site-level as well as the survey- (i.e. site-by-occasion) level in detection. So, for each data set we first randomly picked a value for the standard deviation of each level of overdispersion from a Uniform distribution on (0, 1), where 0 denotes the absence of that component of overdispersion and 1 means a lot of overdispersion. Thus, we intend our simulation to represent a broad assessment of the two methods for assessing the regional total ( $N_{total}$ ) under the  $p$ -ignorant and the overdispersion-naïve approaches against a very broad range of conditions in terms of the type of process that creates counts (i.e., coming from the abundance part of the data-generating processes or from the detection part or from both) and of the magnitude of the associated noise that is introduced into the counts.

This appendix contains the R and JAGS code to execute the full simulation and also, at the end, presents some brief results.

```

library(AHMbook)
?simNmix                                # Check how sim function works

# Create R objects to save results
# -----
simrep <- 1000                            # Number of simulation reps

# True values etc
sigma.vals <- array(NA, dim = c(simrep, 3))
colnames(sigma.vals) <- c('sigma.lam', 'sigma.p.site',
  'sigma.p.survey')
true.Nsite <- array(NA, dim = c(data$nsite, simrep))
true.Ntotal <- numeric(simrep)

# p-ignorant estimators for Nsite and Ntotal
maxCount <- array(NA, dim = c(data$nsite, simrep))
sumMaxCount <- numeric(simrep)

# posterior summaries of everything
# NOTE: this requires one to have fit the model below once before
# You have to manually pick some of the code below first to create
# a data set and analyse it
posterior.summaries <- array(NA, dim = c(dim(fm$summary), simrep))
dimnames(posterior.summaries) <- list(rownames(fm$summary),
  colnames(fm$summary), NULL)
STRETCH.CRI <- array(NA, dim = c(2, simrep))
dimnames(STRETCH.CRI) <- list(c(c('Stretch Lower', 'Stretch
Upper')), NULL)

# Launch simulation
for(i in 1:simrep){

  cat(paste('\n\n*** Simrep Number', i, '***\n\n\n'))

  # Simulate a data set with OD
  # -----
  # pick a random value for the three types of OD that make sense
  for the parrots
  ( sigma.lam <- runif(1, 0, 1) )
  ( sigma.p.site <- runif(1, 0, 1) )
  ( sigma.p.survey <- runif(1, 0, 1) )

  # Simulate a data set using these values
  data <- simNmix(nsites = 130, nvisits = 2, mean.lam = 120, mean.p
= 0.7,
    sigma.lam = sigma.lam, sigma.p.site = sigma.p.site,
    sigma.p.survey = sigma.p.survey, show.plot = FALSE)
  summary(c(data$C))      # summary of observed counts
  summary(exp(data$log.lam)) # summary of lambda

  # Now we fit the model to this data set,
  # ignoring the extra-sources of dispersion
  # -----

```

```

# Data object
str(bdata <- list(counts = data$C, nsites = nrow(data$C),
nsurveys = ncol(data$C))

# Specify model in BUGS language
cat(file = "model.txt", "
model {
  #Priors
  lambda ~ dgamma(0.001, 0.001)
  p ~ dunif(0,1)

  # Biological model for true abundance
  for(i in 1:nsites){
    N[i] ~ dpois(lambda)
    for(j in 1:nsurveys){
      #Observed data at replicated counts
      counts[i,j] ~ dbin(p, N[i]) #counts follow binomial
distribution
      ## Commands for computing Bayesian p-value
      eval[i,j] <- p * N[i]
      E[i,j] <- pow((counts[i,j] - eval[i,j]), 2) / (eval[i,j]
+ 0.001)
      # Pearson GoF statistic
      # Generate replicate data and compute fit stats
      C.new[i,j] ~ dbin(p, N[i])
      E.new[i,j] <- pow((C.new[i,j] - eval[i,j]),2) /
(eval[i,j] + 0.001) # Pearson GoF statistic
    }
  } #sites

  # Fit assessments
  fit <- sum(E)
  fit.new <- sum(E.new)
  c.hat <- fit / fit.new

  # Total abundance across all sites
  Ntotal <- sum(N[])
}
")

# Initial Values
Nst <- apply(data$C, 1, max, na.rm=TRUE) + 1
inits <- function(){list(N=Nst)}

# Parameters monitored
params <- c("N", "Ntotal", "lambda", "p", "fit", "fit.new",
"c.hat")

# MCMC settings
na <- 1000; nc <- 3; nb <- 3000; ni <- 10000; nt <- 7

# Call JAGS

```



```

fm <- jags(bdata, inits, params, "model.txt", n.adapt = na,
n.chains = nc,
          n.thin = nt, n.iter = ni, n.burnin = nb, parallel =
TRUE)

# Now stretch the posterior for Ntotal by sqrt(c.hat)
# And then check the coverage of the stretched CRIs

# Step 1: subtract the mean of the posterior draws
draws <- fm$sims.list$Ntotal # make a copy
cent.draws <- draws - fm$mean$Ntotal

# Step 2: stretch
cent.stretched.draws <- cent.draws * sqrt(fm$mean$c.hat)

# Step 3: put back the mean and compute stretched CRIs
stretch.draws <- cent.stretched.draws + fm$mean$Ntotal
stretch.CRI.Ntotal <- quantile(stretch.draws, prob = c(0.025,
0.975))

# Save all that we need
sigma.vals[i, ] <- c(sigma.lam, sigma.p.site, sigma.p.survey)
true.Ntotal[i] <- data$Ntotal

# p-ignorant estimators for Nsite and Ntotal
maxCount[,i] <- apply(data$C, 1, max)
sumMaxCount[i] <- data$summax

# posterior summaries of everything
posterior.summaries[, ,i] <- fm$summary
STRETCH.CRI[,i] <- stretch.CRI.Ntotal

} # simrep

## Present the results
# -----
# Quick and dirty check whether things have generally converged
hist(posterior.summaries[,8,]) # ... OK

# (1) Results for coverage of the stretched CRI ad-hoc procedure
# -----
inside <- numeric(simrep)
for(i in 1:simrep){
  inside[i] <- (true.Ntotal[i] > STRETCH.CRI[1,i]) *
(true.Ntotal[i] < STRETCH.CRI[2,i])
}

mean(inside)
[1] 0.633

```

Hence, the mean coverage of the stretched CRIs for Ntotal is only 0.633, which is a long way from 0.95, but it is without a doubt much better than what we would obtain without stretching the CRIs.

```
# (2) Results for estimation error of p-ignorant vs. OD-naive
Nmix:
#   Would we do better by simply taking the max counts ?
# -----
-

# For the total N across all sites: Ntotal
# -----
# Compare Mean total error for both approaches
(RMSE.total.counts <- sqrt(mean(sumMaxCount - true.Ntotal)^2) )
(RMSE.total.Nmix <- sqrt(mean(posterior.summaries[131,1,] -
true.Ntotal)^2) )

# [1] 4929.368          # max counts
# [1] 3720.835          # OD naive Nmix

round((3720.835 - 4929.368) / 4929.368, 4)      # minus 25% in
error when using Nmix over counts
```

Hence, averaged over all the overdispersion scenarios represented by the 1000 realizations from our data-simulation process, we expect to have 25% less total estimation error (in the root mean squared error sense) when using an overdispersion-naive binomial N-mixture model than when using a p-ignorant approach where we simply add up the maximum counts across sites.

This result was decisive for our choice to use an N-mixture model for inference about parrot total population size even when that model did not pass our Goodness of fit tests.

We do, however, not recommend such an approach in general and emphasize once more the ad hoc nature of our procedure. We believe this is the right approach for our data set and objectives, but that may not be true for other studies!

## References

Kéry, M., Royle, J.A., Meredith, M., 2020. AHMbook: Functions and Data for the Book “Applied Hierarchical Modeling in Ecology” Vols. 1 and 2. Available at: <https://www.mbr-pwrc.usgs.gov/pubanalysis/keryroylebook/> and <https://sites.google.com/site/appliedhierarchicalmodeling/home>

**6. CAPÍTULO 2: Integrating citizen-science and planned-survey data improves species distribution estimates**

Artigo publicado na revista *Diversity and Distributions*.

# Integrating citizen-science and planned-survey data improves species distribution estimates

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## Funding information

Instituto Humanize; Programa de Internacionalização (PrInt/CAPES); Fundo Brasileiro para a Biodiversidade (FUNBIO); Coordenação de Aperfeiçoamento de Pessoal de Nível Superior; Conselho Nacional de Desenvolvimento Científico e Tecnológico, Grant/Award Number: PP 312606/2013-3; The Rufford Foundation, Grant/Award Number: 19835-1 and 23709-2

Editor: Martin Jung

## Abstract

**Aim:** Mapping species distributions is a crucial but challenging requirement of wild-life management. The frequent need to sample vast expanses of potential habitat increases the cost of planned surveys and rewards accumulation of opportunistic observations. In this paper, we integrate planned-survey data from roost counts with opportunistic samples from eBird, WikiAves and Xeno-canto citizen-science platforms to map the geographic range of the endangered Vinaceous-breasted Parrot. We demonstrate the estimation and mapping of species occurrence based on data integration while accounting for specifics of each dataset, including observation technique and uncertainty about the observations.

**Location:** Argentina, Brazil and Paraguay.

**Methods:** Our analysis illustrates (a) the incorporation of sampling effort, spatial autocorrelation and site covariates in a joint-likelihood, hierarchical, data integration model; (b) the evaluation of the contribution of each dataset, as well as the contribution of effort covariates, spatial autocorrelation and site covariates to the predictive ability of fitted models using a cross-validation approach; and (c) how spatial representation of the latent occupancy state (i.e. realized occupancy) helps identify areas with high uncertainty that should be prioritized in future fieldwork.

**Results:** We estimate a Vinaceous-breasted Parrot geographic range of 434,670 km<sup>2</sup>, which is three times larger than the “Extant” area previously reported in the IUCN Red List. The exclusion of one dataset at a time from the analyses always resulted in worse predictions by the models of truncated data than by the Full Model, which included all datasets. Likewise, exclusion of spatial autocorrelation, site covariates or sampling effort resulted in worse predictions.

**Main conclusions:** The integration of different datasets into one joint-likelihood model produced a more reliable representation of the species range than any individual dataset taken on its own, improving the use of citizen-science data in combination with planned-survey results.

## KEYWORDS

citizen-science, data integration models, endangered species, geographic range, occupancy models, species distribution models, Vinaceous-breasted Parrot

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## 1 | INTRODUCTION

Wildlife management depends on knowledge about species' geographic ranges, which is also a key element of threat assessment criteria used by the International Union for Conservation of Nature (IUCN, Mace et al., 2008). Despite their unequivocal relevance, accurate range maps are scarce (Jetz et al., 2012). Efforts to improve knowledge about species ranges are hindered by the extent of necessary field sampling and by the scarcity of funding for monitoring. The sampling challenge is heightened by the inevitable trade-off between data quantity and quality. Planned surveys with replicated samples of a predetermined set of locations using standardized protocols that note the presence or absence of target species provide high-quality information, but they are few and far between. Large and long running planned surveys such as the North American Breeding Bird Survey (BBS; Hudson et al., 2017) or the Pan-European Common Bird Monitoring scheme (PECBM; Gregory et al., 2005) are exceptions to a global pattern of "opportunistic" collection of mostly presence-only data, which records where a species is detected but not where it is searched for and not found, in contrast with presence-absence data, which records where a species is and where it is not detected.

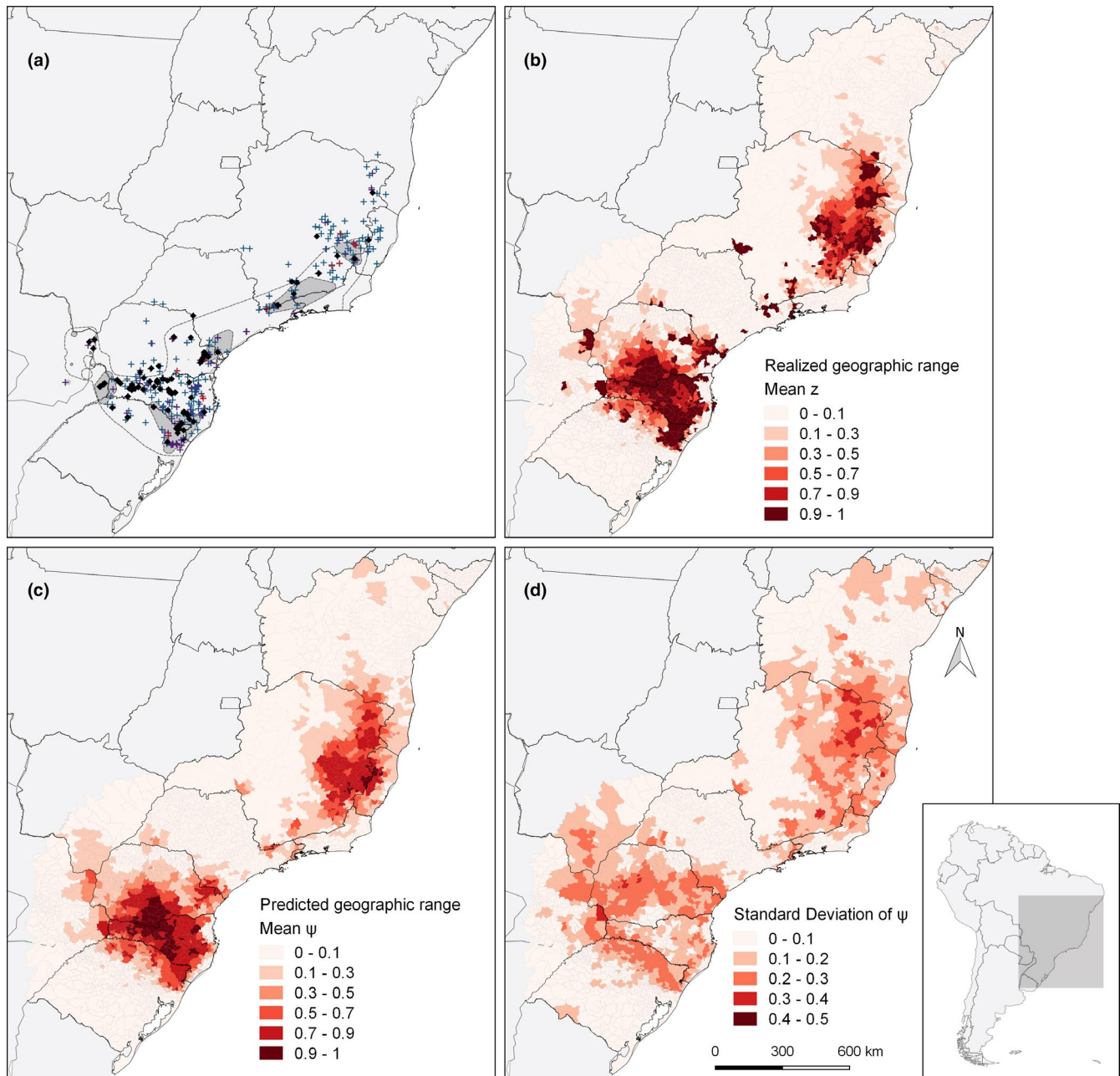
Technological advances have produced many collaborative initiatives where volunteers share wildlife sightings from opportunistic records in easily accessible online platforms. These initiatives fall under the broad umbrella of citizen science (Heigl et al., 2019; Tulloch, 2013; Wiggins & Crowston, 2011). Due to the popularity of birdwatching, citizen-science platforms now hold an extraordinary amount of spatially indexed bird detections. Outstanding examples include the global eBird (Sullivan et al., 2009) and Xeno-canto (Xeno-canto, 2019) platforms, as well as the Brazilian WikiAves (WikiAves, 2019). These platforms hold data for thousands of bird species, with increasing spatial coverage. These huge datasets have the potential to fill gaps in our knowledge of species' distributions (Altwegg & Nichols, 2018; La Sorte & Someville, 2020; Sullivan et al., 2017). There are, however, wide variations in sampling technique, expertise, and effort among observers, as well as differences in data structures and spatial coverage among citizen-science platforms. The ability to integrate data from different sources is therefore important. This has spurred progress in the construction of statistical species distribution models that integrate multiple data streams for mapping the probability of species presence over a region of interest (Fletcher et al., 2019; Isaac et al., 2020; Miller et al., 2019).

Initial work on data integration methods used presence-absence datasets as an accessory to the analyses of larger presence-only datasets. Seminal papers by Dorazio (2014), Fithian et al. (2015), and Giraud et al. (2016) integrated presence-only data from opportunistic samples with presence-absence data from planned surveys in a spatial point-process, joint-likelihood framework. The resulting data integration models use the sampling effort information in presence-absence data to improve inference from the usually larger, presence-only datasets that lack information about effort. This approach has

been extended to account for local habitat heterogeneity (Coron et al., 2018) and data patchiness (Peel et al., 2019). In one wide-ranging study, Pacifici et al. (2017) showed how data integration can include site covariates, account for spatial autocorrelation, address false positive detections, combine counts with presence-absence data and weigh datasets differently based on their quality. Simmonds et al. (2020) recently explored the limits of data integration, asking when more data are not necessarily better. These efforts demonstrated how data integration can not only account for limitations of presence-only data, but also flexibly and robustly harmonize a wide-range of data types (Isaac et al., 2020; Miller et al., 2019).

The early emphasis on integrating widely available, opportunistic data from citizen-science sources with explicit sampling information from planned-survey, presence-absence data may have concealed the extraordinary amount of sampling information contained in citizen-science datasets themselves (but see previous analyses of sampling information from citizen-science sources, e.g. Kéry et al., 2010). The set of data points indicating detection of one focal species in a citizen-science platform may not explicitly convey the effort that went into searching for that species; nonetheless, because platforms gather observations from multiple species, one can find abundant information about sampling effort by looking at where and when non-focal species were detected (Hill, 2012; Phillips et al., 2009). Indeed, citizen-science data frequently include information that can be used to estimate sampling effort, such as number of observers, time and distance travelled during sampling, number of detections of all species or number of species detected. Here, we build on previous work by Fithian et al. (2015), Pacifici et al. (2017), Stauffer et al. (2018) and Miller et al. (2019), to develop a static, integrated occupancy model of species distribution. Our approach assembles detection non-detection information for each sampling unit and accounts for imperfect detection within each data source in the integrated model via the estimation of sampling effort per source. To assess the extent to which our accounting of sampling effort improves distribution models, we employ a cross-validation approach that measures the ability of different models to predict randomly excluded data points. Such assessment of model fit also reveals the extent to which data integration, spatial autocorrelation and site covariates contribute to the modelling task.

Accurate range maps are especially needed for threatened or endangered species in regions that lack planned wildlife surveys, as is often the case in the tropics. The Vinaceous-breasted Parrot (VBP, *Amazona vinacea*) is an endangered species, endemic to the tropical South American Atlantic Forest (BirdLife International, 2017). Showing substantial uncertainty about the species' geographic range, the IUCN reports a "possibly extant" VBP area that is almost three times as large as the "extant" area (Figure 1a, BirdLife International & Handbook of the Birds of the World, 2016). In a recent study of VBP abundance, Zulian et al. (2020) show how ~75% of known communal roost sites are outside the IUCN "extant" area, suggesting current range estimates are inadequate for planning purposes. This motivated us to ask how VBP data sources could be combined to generate a better estimate of the species' range and identify



**FIGURE 1** Vinaceous-breasted Parrot observations, geographic distribution and uncertainty about the distribution. Panel a maps Vinaceous-breasted Parrot detections analysed in this study with black diamonds indicating the location of roost counts and crosses the location of citizen-science (eBird-in red, WikiAves-in blue and Xeno-canto-in purple) records. Grey polygons represent the IUCN “Extant” range and dashed lines delimit the IUCN “Possibly Extant” range of the Vinaceous-breasted Parrot. Panel b represents realized occupancy (mean  $z$ ). Panels c and d show, respectively, the predicted occupancy ( $\psi$ ) and the standard deviation of its posterior distribution. Estimates in panels b, c and d are based on the Full Model fit to all (roost counts, eBird, WikiAves and Xeno-canto) datasets. Spatial units correspond to municipalities, with darker tones of red representing higher occupancy (b, c) and higher standard deviation (d)

where the greatest uncertainty in the current distribution exists. We set out to characterize the spatial extent of the current distribution, estimating the local probability of the species’ presence (Kéry, 2011) and quantifying the uncertainty about these probability estimates (Rocchini et al., 2011).

We aim here to (a) demonstrate how data integration models can be harnessed to address differences in data collection across

multiple datasets by accounting for variation in sampling effort and detection probability between and within datasets; (b) develop an approach to assess the predictive value of including or excluding different data streams in a single integrated model; and (c) assess how modelling decisions affect the predictive power of our models, with particular attention to the choice of occupancy and detection covariates, whether and how to account for residual spatial

autocorrelation, and how effort and detection are related. We integrate planned-survey data collected by research teams (Zulian et al., 2020) with citizen-science data from the eBird (eBird, 2019), WikiAves (WikiAves, 2019) and Xeno-canto (Xeno-canto, 2019) platforms to model the VBP geographic range in an eleven-year period.

## 2 | METHODS

### 2.1 | Study area

Our study area comprises 2,449,757 km<sup>2</sup> divided into 3,701 municipalities from Argentina, Brazil and Paraguay (Figure 1a). This area includes the entire IUCN-delimited VBP "Possibly Resident" range (BirdLife International & Handbook of the Birds of the World, 2016) and is bounded by the limits of the Atlantic Forest biome (Olson et al., 2001). Considering the absence of VBP records north of the Brazilian state of Bahia (BirdLife International, 2017), we set the northern limit of our study area along the northern borders of that state and the adjacent state of Alagoas.

### 2.2 | Data collection

We obtained VBP detection–non-detection data for all 3,701 municipalities collected between 1 January 2008 and 31 December 2018. We chose the municipality as our spatial unit because WikiAves data register the location of observations by municipality name, without spatial coordinates and because municipality limits are easily recognized by decision-makers and residents. "Occupancy" is given by the presence of VBPs in a municipality during the eleven-year study period. Our data come from four sources: roost counts, WikiAves, eBird and Xeno-canto. Roost counts were performed by researchers (Zulian et al., 2020), while WikiAves, eBird and Xeno-canto data were uploaded to citizen-science platforms by volunteer observers.

Roost counts were performed between 2014 and 2018 by 26 teams in 74 municipalities of Brazil, Argentina and Paraguay, following methodological guidelines described by Zulian et al. (2020). Between one and 25 counts per site were taken each year, between April and June, on sites known by researchers to have VBP roosts. Roost count data were converted into detection/non-detection histories with counts from the same municipality considered as replicate samples. Counts with at least one parrot received a "1" (detection) and counts with no parrots received a "0" (non-detection) in the binary history. Parrots are observed in relatively narrow time windows near dawn and dusk, but early arrivals or a late departure from the roost influence the observations, so we measured the count's duration in minutes (Time Observing = TObs) as an effort covariate.

We obtained eBird data from birding checklists with observations in our study area and uploaded to the platform throughout the study period. Our analysis included only complete checklists—where the observers recorded all the species they were able to identify—and excluded all checklists, which did not identify a

municipality or that potentially spanned more than one municipality due to long distance (>12 km) or long time (>360 min) travelled. Checklists from the same municipality were treated as replicate samples. The checklist structure made it easy to convert eBird data into detection/non-detection format, and we accordingly built eBird detection/non-detection histories that register the detection (1) or non-detection (0) of the VBP for each list of each municipality. eBird effort covariates were the number of species recorded in a list (*SSee*), minutes spent observing (*TObs*) and kilometres travelled (*RLen*).

WikiAves receives observer input in the form of individual photographs or audio recordings of an identified species and has expert moderators checking uploaded content to avoid misidentification. Record location is registered as a municipality name along with information about authorship and comments. We obtained the total number of WikiAves records uploaded to each municipality of our study area and period, and recorded detection/non-detection as only one data point per municipality, without replication at the municipality level. Thus, there is only one vector of WikiAves detection/non-detection data, with length equal to the number of municipalities and values of "1" or "0," respectively, for those municipalities that did or did not have at least one VBP photograph or audio recording. Effort covariates were the number of photos (*NPho*) and audio recordings (*NAud*) submitted to WikiAves per municipality.

Xeno-canto hosts only audio recordings of bird sounds (Xeno-canto, 2019). We used the R package *warbleR* (Araya-Salas & Smith-Vidaurre, 2017) to download the list of all Xeno-canto records from our study area and period. Our Xeno-canto unit data are the set of all audio recordings from one municipality, without replication. We organized these detection/non-detection data in the same vector format as WikiAves' and used the number of recordings (*NAud*) uploaded in each municipality as a covariate of sampling effort. Unlike WikiAves, Xeno-canto does not have its content checked by moderators, but we did confirm identification of all Xeno-canto VBP records. Unlike eBird, neither Xeno-canto nor WikiAves records can be organized as complete lists of every species that an observer identified in a given space and time.

### 2.3 | Data analysis

We summarized each of our four data sources in a matrix or a vector of detection–non-detection information per municipality, depending, respectively, on whether they had multiple (roost counts, eBird) or a single (WikiAves, Xeno-canto) observation per municipality. Effort covariates matrices (or vectors) took the corresponding data source shape. In our models, the true occupancy state of each municipality (or site)  $i$  is denoted as  $z_i$ , which takes the value 1 when site  $i$  was occupied and 0 when not. The state of this latent (partially observed) variable follows a Bernoulli distribution with mean  $\psi_i$ :

$$z_i \sim \text{Bernoulli}(\psi_i). \quad (1)$$

We allowed the probability  $\psi_i$  that site  $i$  is occupied by VBPs to vary with respect to three site environment covariates, with a logit link function. As VBPs are endemic to the Atlantic Forest and appear to be associated with both altitude (BirdLife International, 2017) and Araucaria forest cover (BirdLife International, 2017; Cockle et al., 2019; Collar et al., 2017; Tella et al., 2016), we included Atlantic forest cover ( $AtF_i$ ), Araucaria forest cover ( $ArF_i$ ) and average altitude ( $Alt_i$ ) as covariates of municipality  $i$  occupancy. Forest cover values are from Ribeiro et al. (*in preparation*) as proportions of the municipality area. Average municipality altitude  $x$ , in metres, is from DIVA-GIS (2018), log-transformed as  $\log(x + 1)$ . Our linear model of occupancy also included a spatial random effect to account for unexplained spatial autocorrelated variation ( $\delta_i$ ):

$$\text{logit}(\psi_i) = \beta_0 + \beta_1 * AtF_i + \beta_2 * ArF_i + \beta_3 * Alt_i + \delta_i. \quad (2)$$

This effect follows a conditional auto-regressive (CAR) distribution as applied by Pacifici et al. (2017) in the context of integrated species distribution models. To avoid confounding effects of municipality size variability and to gain sampling replication within spatial units in the CAR analysis, we represented space by a hexagonal lattice overlaid on the study area, with municipalities assigned to the lattice cell that matches their centroid. Cells measured 0.5° latitude across; all the first-order neighbours of each cell were given a weight of 1 when fitting the CAR model.

We fit a joint-likelihood data integration model with a single shared occupancy process: for all four data types, VBP detection in sample  $j$  and site  $i$  is conditional on the species being present at the site ( $z_i = 1$ ). Departing slightly from the standard accounting of effort based on the number of replicate samples (MacKenzie et al., 2002), we express the conditional probability ( $p_j^*$ ) of detecting the species as a function of an estimated amount of sampling effort ( $E_j$ ) for sample  $j$  (Miller et al., 2019; Stauffer et al., 2018):

$$p_j^* = 1 - (1 - p)^{E_j}, \quad (3)$$

where  $p$  is the probability of detection per unit effort. Because we are using indirect, and sometimes several metrics of effort for each data source (our effort covariates), we estimate parameter  $E_j$  for each sample  $j$  as a linear function of the covariates. Thus, for each data source (RC = roost counts, EB = eBird, WA = WikiAves and XC = Xeno-canto) we have:

$$E_j^{RC} = \alpha_1 * TObs_j \quad (4a)$$

$$E_j^{EB} = \alpha_2 * SSee_j + \alpha_3 * TObs_j + \alpha_4 * RLen_j \quad (4b)$$

$$E_j^{WA} = \alpha_5 * NPho_j + \alpha_6 * NAud_j \quad (4c)$$

$$E_j^{XC} = \alpha_7 * NAud_j. \quad (4d)$$

Equations (4a–d) have no intercept, so that effort is 0 when all effort covariates are 0. In addition, we fix  $p$  at a value of .5, so that the  $\alpha_1 - \alpha_7$  coefficients express the relationship between covariates and the effort necessary to reach a detection probability of .5 per unit of effort. Without fixing  $p$ , Equation (3) becomes over-parameterized. Coefficients  $\alpha_1 - \alpha_7$  of the effort functions also show the relative contribution of each covariate to the total estimated effort per dataset (see code in Appendix S1). Finally, our detection/non-detection histories  $Y_{ij}$  in each dataset follow the Bernoulli distribution:

$$Y_{ij} \sim \text{Bernoulli}(z_i \times p_j^*). \quad (5)$$

We first fitted a Full Model accounting for the effects of all effort metrics, all site covariates and spatial autocorrelation. Subsequently, we evaluated the impact of different modelling decisions on predicted accuracy by fitting 11 additional models listed in Table 2. We fitted all the models using a Bayesian estimator coded in the BUGS language and run on WinBugs software (Lunn et al., 2000), which includes predefined model structures for CAR random effects. Inference was based on draws from the posterior distribution of model parameters using an MCMC algorithm with three chains, 200,000 iterations, and a burn-in phase of 100,000. We considered parameters with an R-hat lower than 1.1 to have converged and used results to draw parameter posterior distributions.

We assessed model fit by excluding all the detection non-detection data from a randomly selected set of 650 municipalities (20% of the total), fitting the models to the training dataset (i.e. remaining data) and then predicting the validation dataset (excluded data) based on the estimated parameters. In this cross-validation approach, our prediction accuracy measures a model's ability to predict excluded data as expressed by the likelihood-based Deviance:

$$D = -2 \sum \log(\mathcal{L}), \quad (6)$$

where the likelihood  $\mathcal{L}$  equals  $\hat{y}^y * (1 - \hat{y})^{1-y}$  for each site and visit in the validation dataset (Hooten & Hobbs, 2015). We use  $y$  and  $\hat{y}$  to represent, respectively, the observed, binary data and the predicted probability of detecting VBPs for each site and visit based on estimates from the training data. The lowest deviance values indicate the best fit. We examined overall model deviance, summed across data sources, as well as individual deviance values for each data source to look at source-specific predictive performance. Comparisons among values also revealed the impact of site covariates, detection covariates and the CAR component on the predictive performance of our models.

To determine whether each of the individual datasets improved the predictive ability of our model, we fit the model to four truncated datasets, including all covariates and the CAR random effect, but excluding one data source at a time (Models 5–8, Table 2). Such rotating exclusion made it possible to examine whether the addition of a data source to the mix improves the model's ability to predict the validation set from other sources. Specifically, we asked whether predictions of validation data from a training data source were more or less accurate when each of the other data sources were excluded.



For example, if eBird does contribute to improving the overall model, then including eBird data should lead to better predictions of Xenocanto, WikiAves and roost count data. This is a measure of overall prediction consistency among data sources. To better assess the usefulness of data integration, we also fit four models that retain the site covariate and CAR components of the Full Model, but include only one data source at a time (Models 9–12, Table 2).

Finally, we represent the VBP geographic range using two estimates of site occupancy. The first, “realized” occupancy, is conditional on the observations; it equals 1 in all municipalities where VBP was seen at least once, and is the expected value of the latent occupancy state ( $z_i$ ) where it was not seen. As effort increases and VBPs are not observed,  $z$  converges towards 0, and so does realized occupancy. Even though  $z_i$  can only be 0 or 1, “realized” occupancy, the expected value of  $z_i$ , obtained by averaging the MCMC chain for  $z$  in site  $i$  can take values between 0 and 1. This metric provides a measure of local uncertainty about species presence given all available data and, unlike typical predictions by distribution models, accurately expresses local certainty of occurrence by adjusting predictions to actual observation. The second estimate, “predicted” occupancy, offers estimates of  $\psi_i$ , which express occupancy probability for a statistical population of municipalities with the same site covariates and neighbourhood of municipality  $i$  (Figure 1c). Predicted occupancy is not conditioned on the actual data for a municipality: unlike  $z_i$ , which always equals 1 if the species was detected at site  $i$ ,  $\psi_i$  can be smaller than 1 in municipalities where the species was detected. Predicted occupancies are typically visualized in distribution models, expressing how estimated environmental relationships affect the local probability of occurrence across a species range.

### 3 | RESULTS

We draw on 1,007 VBP detections from 47,240 samples in four datasets collected across the 3,402 municipalities within our study area (Table 1). While the roost count data contains 40% of all detections, roost counts covered only 2.2% of the municipalities in our study area. The highest detection rate—given by the ratio of  $n_{\text{det}}$  to

Sample size, in Table 1—appears in the roost count dataset (88%), as expected, because roost counts were only carried out in locations where VBPs were known to occur. This resulted in the highest detection probability per sample among all datasets ( $p = .87 \pm .144$ ; Table 1). The 596 detections jointly returned by the three citizen-science platforms, on the other hand, come from 3,401 municipalities, 92% of the number of municipalities in the study area. WikiAves had the widest coverage, with data for 3,190 municipalities, and VBP detections for 191 of them. One WikiAves sample comprises all the photographs and recordings submitted for one municipality, a large amount of effort per sample, so WikiAves had the highest detection rate and, naturally, the highest detection probability per sample of all citizen-science sources. eBird had smaller coverage than WikiAves but had the largest number of VBP detections of all sources: 388 from 71 municipalities. Differently from WikiAves (and Xenocanto), one eBird sample is not the set of all records in one municipality, but one birding list. The number of eBird samples varied substantially across municipalities, ranging from 1 to 3,244 (São Paulo, SP, Brazil) with a mean of 42. With so many samples and relatively little effort per sample, eBird had the lowest detection rate, of 1%, and the lowest estimated detection probability of all platforms ( $p = .06 \pm .003$ ; Table 1). Xenocanto, with the smallest coverage and number of VBP detections had intermediate values of both detection rate and estimated  $p$ .

Table 2 shows model predictive ability based on cross-validation. The Full Model had the best predictive ability. Exclusion of detection covariates (Model 3) had the greatest negative impact on predictive ability, with estimated deviance being 2.15 times higher for this model than for the Full Model (Table 2). Removal of the CAR component (Model 2) had an intermediate but measurable effect on deviance, with residual spatial structure (Figure S1) visibly influencing the distribution map (Figure S2). The values in Table 2 result from one trial of data exclusion and prediction. We performed another two trials of this procedure for the first four models in Table 2 with consistent results for total deviance. The ranking of models with respect to specific dataset deviances changed between trials, but it showed a tendency for better prediction with the Full Model and worse prediction when detection covariates are excluded (Table S1).

| Datasets | Sample size | Coverage | $n_{\text{det}}$ | $n_{\text{muni}}$ | Sampling unit | $p$            |
|----------|-------------|----------|------------------|-------------------|---------------|----------------|
| RC       | 466         | 74       | 411              | 60                | Count         | $.87 \pm .144$ |
| EB       | 42,855      | 1,274    | 388              | 71                | List          | $.06 \pm .003$ |
| WA       | 3,190       | 3,190    | 191              | 191               | Municipality  | $.25 \pm .011$ |
| XC       | 729         | 729      | 17               | 17                | Municipality  | $.08 \pm .015$ |
| Total    | 47,240      | 3,402    | 1,007            | 339               |               |                |

**TABLE 1** Sample size, spatial coverage and number of Vinaceous-breasted Parrot detections from roost counts (RC), eBird (EB), WikiAves (WA) and Xenocanto (XC)

Note: Sample size is number of samples, following each database's sampling unit definition. Spatial coverage is the number of municipalities sampled, with total smaller than the sum across databases because some municipalities are included in more than one database. Labels  $n_{\text{det}}$  and  $n_{\text{muni}}$  show, respectively, the number of parrot detections and the number of municipalities with at least one detection. The sampling unit is the data category considered as a replicate;  $p$  is estimated detection probability per sampling unit at average effort for each dataset, under the Full Model.

**TABLE 2** Deviance for each site-occupancy model in this study

| Models                | Total deviance | Deviance in each dataset |               |               |              |
|-----------------------|----------------|--------------------------|---------------|---------------|--------------|
|                       |                | RC                       | EB            | WA            | XC           |
| <b>1. Full Model</b>  | <b>440.85</b>  | <b>28.84</b>             | <b>281.19</b> | <b>103.35</b> | <b>27.46</b> |
| 2. No CAR             | 581.32         | 50.97                    | 362.58        | 139.56        | 28.20        |
| 3. No detection covs. | 952.84         | 57.21                    | 735.61        | 133.60        | 26.41        |
| 4. No occupancy covs. | 477.06         | 26.04                    | 315.34        | 107.79        | 27.87        |
| 5. All data but RC    | –              | –                        | 301.88        | 108.78        | 27.56        |
| 6. All data but EB    | –              | 28.53                    | –             | 110.26        | 25.55        |
| 7. All data but WA    | –              | 35.27                    | 326.01        | –             | 28.61        |
| 8. All data but XC    | –              | 34.04                    | 309.29        | 116.18        | –            |
| 9. Only RC            | –              | 23.22                    | –             | –             | –            |
| 10. Only EB           | –              | –                        | 314.78        | –             | –            |
| 11. Only WA           | –              | –                        | –             | 107.75        | –            |
| 12. Only XC           | –              | –                        | –             | –             | 28.77        |

Note: Model 1, designated as “Full Model,” includes detection as well as occupancy covariates and was fitted to data from all datasets: roost counts (RC), eBird (EB), WikiAves (WA) and Xeno-canto (XC). Model 2 equals model 1 without spatial autocorrelation. Models 3 and 4 are variants of model 1 without, respectively, detection and occupancy covariates. Models 5–8 differ from the Full Model by the exclusion of one dataset each, as shown. Models 9–12 are each fitted to an individual dataset alone. As models 5–12 do not use the same data, their Total Deviance is not comparable and is omitted from the table. Bold font highlights the model with the best fit by Total Deviance. Contrast the values on line 1 with those on lines 5–12 to see sixteen possible comparisons between the Full Model fit to all four datasets (line 1) and the same model fit to different combinations of datasets (lines 5–12).

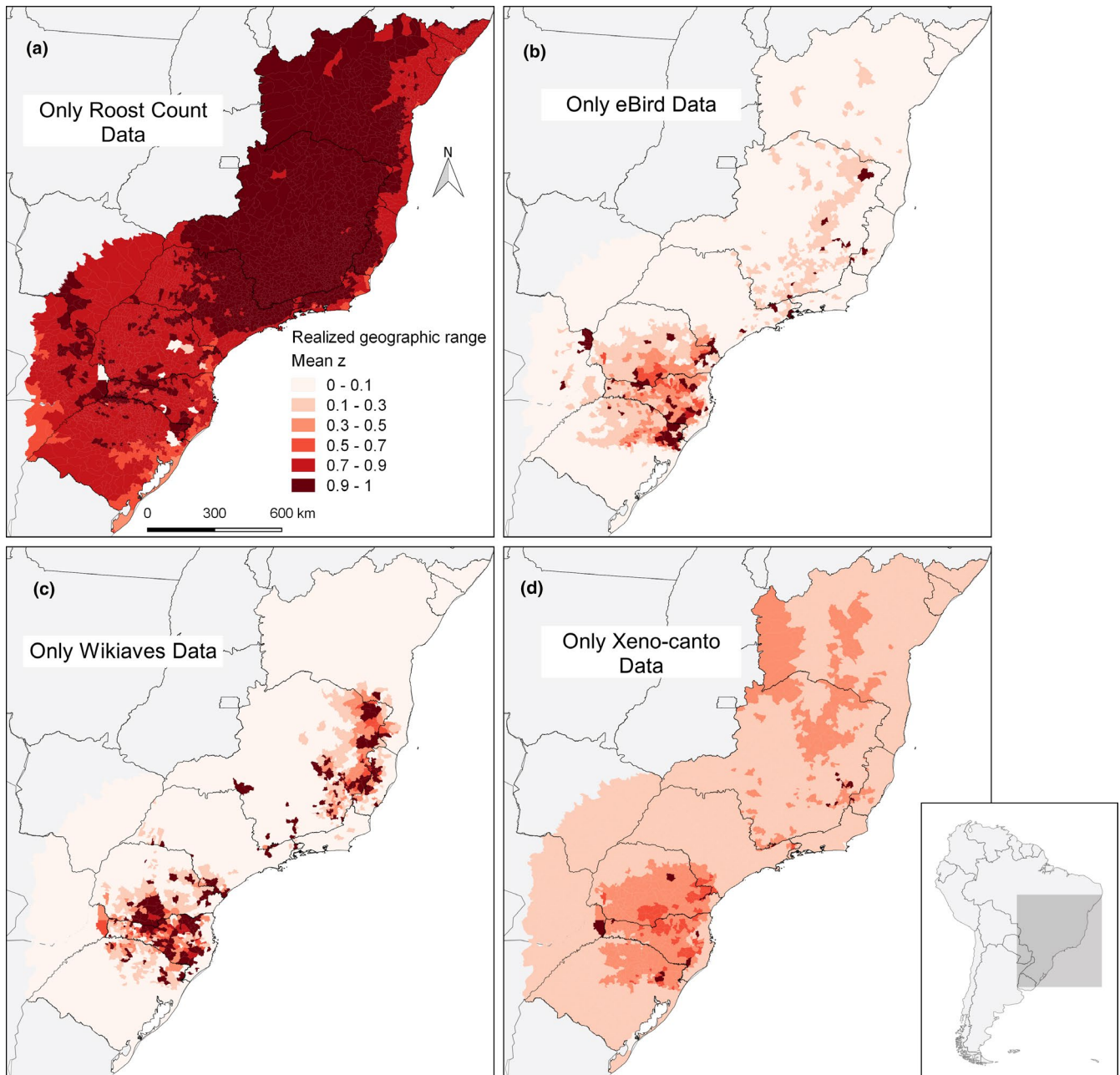
Our results reveal that effort-based modelling of detection, inclusion of spatial autocorrelation in occupancy, and consideration of occupancy covariates improved the predictive ability of our species distribution models.

Models 5–8 assess whether individual datasets improve overall predictive ability. We compare dataset-specific deviances from the validation data for each of the four models to that of the Full Model (where no data were excluded). Including the four datasets in the analysis (i.e. using the Full Model) improved fit in all but two cases. Dataset-specific deviances of Models 5, 7 and 8 were all higher—indicating lower prediction power—than those of the Full Model (Table 2). Removal of eBird data (Model 6) slightly improved the prediction of Xeno-canto data, but clearly worsened the fit to WikiAves data, leaving that of the roost count data virtually unchanged. The Full Model fit to all data sources did a better job of predicting EB, WA, and XC data than the individual-dataset Models 10–12 themselves. Model 9, which was fit to RC data alone, predicted RC validation data better than the Full Model, but it produced an incongruous realized range map (Figure 2a), with mean  $z$  values in excess of 0.9 for hundreds of municipalities where other datasets produced mean  $z$  smaller than 0.3 (Figure 2b–d). The realized range map obtained under Model 10, of the EB data alone, missed a large part of the northern VBP distribution (Figure 2b). Data integration under the Full Model improved the prediction of EB validation data more than the prediction for any other dataset.

The sum of municipality areas weighted by the Full Model realized occupancy estimates returned a realized VBP range of

434,670 km<sup>2</sup>, which is three times larger than the IUCN Red List “Extant” area (BirdLife International & Handbook of the Birds of the World, 2016). Both the realized and the predicted ranges appear split in two large patches (Figure 1b,c). The southern patch covers parts of Argentina, Paraguay and the Brazilian states of Rio Grande do Sul, Santa Catarina and Paraná; the northern patch overlaps the Brazilian states of Minas Gerais, Espírito Santo and Bahia. The realized range also includes small areas between the two large patches, mainly in the Campos do Jordão region, near the border between São Paulo and Minas Gerais (Figure 1b). Uncertainty about the VBP range is greatest around high-occupancy patch edges, as shown by intermediate values of realized occupancy (Figure 1b) and high standard deviation of predicted occupancy (Figure 1d). As expected, municipalities with the most extreme occupancy values (close to 0 or 1) returned the lowest standard deviation values (Figure 1d).

Araucaria and Atlantic forest cover had strong (and positive) effects on occupancy probability (Table 3). Altitude had a weaker, positive, but more precise effect on  $\psi$ , when compared with the two forest covariates. The different effort covariates on the bottom part of Table 3 had varying, though always positive, effects on detection probability. Among these, time spent observing showed the highest effect, both as  $\alpha_1$ , which measures the duration of a roost count, and as  $\alpha_3$ , the time spent collecting an eBird list. The number of audio recordings uploaded in WikiAves was a stronger predictor of survey effort ( $\alpha_6$ ), and thus overall detection probability for a municipality, than the number of photos (with effect  $\alpha_5$ ).



**FIGURE 2** Vinaceous-breasted Parrot realized geographic range (mean  $z$ ) based on separate analyses of each dataset. The panels show results based on roost count (a), eBird (b), Wikiaves (c) and Xeno-canto (d) data. Spatial units correspond to municipalities, with darker tones of red representing higher mean  $z$ ; intermediate values—of  $z \sim 0.5$ —indicate the highest uncertainty about occupancy

#### 4 | DISCUSSION

The Vinaceous-breasted Parrot geographic range covers approximately 434 thousand square kilometres subdivided into two large patches, one centred in the southern Brazilian state of Santa Catarina and another to the north, centred in eastern Minas Gerais state, also in Brazil. A third, much smaller area of occupancy comprises a group of relatively high-altitude municipalities near Campos do Jordão, in São Paulo and Minas Gerais states, approximately 100 km west of the Rio de Janeiro border. Our two-patch range contrasts with the

five patches represented in the IUCN “resident” range. The “possibly resident” IUCN range, which encloses all of the “resident” patches, conveys uncertainty about the subdivision in five areas (BirdLife International & Handbook of the Birds of the World, 2016). Our study provides evidence for redrawing the VBP range while quantifying uncertainty associated with the new map. We look forward to seeing population genetic studies that elucidate the extent of reproductive isolation between the two large patches, as well as between the small Campos do Jordão area and the northern, Minas Gerais patch. A comparison between realized and predicted ranges

**TABLE 3** Estimated mean, standard deviation (SD) and 95% credible intervals (CI) for the posterior distribution of Full Model coefficients

| Parameter                          | Mean $\pm$ SD      | 95% CI      |
|------------------------------------|--------------------|-------------|
| <i>Biological process</i>          |                    |             |
| $\beta_1$ (Atlantic forest cover)  | 2.110 $\pm$ 0.8684 | 0.379–3.792 |
| $\beta_2$ (Araucaria forest cover) | 2.133 $\pm$ 0.9806 | 0.296–4.104 |
| $\beta_3$ (Altitude)               | 0.852 $\pm$ 0.1205 | 0.579–1.055 |
| <i>Sampling process</i>            |                    |             |
| $\alpha_1$ (RC: Time observing)    | 1.814 $\pm$ 0.1110 | 1.613–2.043 |
| $\alpha_2$ (EB: Species seen)      | 0.002 $\pm$ 0.0002 | 0.001–0.002 |
| $\alpha_3$ (EB: Time observing)    | 0.008 $\pm$ 0.0027 | 0.003–0.013 |
| $\alpha_4$ (EB: Route length)      | 0.005 $\pm$ 0.0019 | 0.002–0.009 |
| $\alpha_5$ (WA: Photos)            | 0.001 $\pm$ 0.0002 | 0.001–0.002 |
| $\alpha_6$ (WA: Audio recordings)  | 0.006 $\pm$ 0.0021 | 0.003–0.011 |
| $\alpha_7$ (XC: Audio recordings)  | 0.007 $\pm$ 0.0017 | 0.004–0.011 |

*Note:* Occupancy function coefficients ( $\beta_1$  to  $\sigma$ ) specify the biological process, while detection coefficients ( $\alpha_1$ – $\alpha_7$ ) specify the sampling process. The covariates corresponding to each coefficient appear in parentheses in front of its name;  $\sigma$  measures the magnitude of spatial autocorrelation in site occupancy. Coefficients  $\alpha_1$ ,  $\alpha_2$ – $\alpha_4$ ,  $\alpha_5$ – $\alpha_6$  and  $\alpha_7$  correspond, respectively, to metrics of effort per municipality in roost counts (RC), eBird (EB), WikiAves (WA) and Xeno-canto (XC) databases. Each metric is indicated in parentheses in front of the coefficient name.

shows that some municipalities with high mean  $z$  have relatively low predicted occupancy probability ( $\psi$ ). We trust the WikiAves moderation system, have no doubts about VBP identification in the roost counts, and manually checked every VBP record from Xeno-canto; but still, we cannot rule out the possibility of some false positive observations in these municipalities. Occasional discrepancy between mean  $z$  and  $\psi$  could also derive from the observation of animals released or escaped from captivity. These municipalities deserve further investigation, particularly those in south-west Minas Gerais and south-west São Paulo, to exclude the possibility of there being unknown isolated populations. Intermediate values of realized occupancy and high standard deviation of the posterior distribution of predicted occupancy reveal areas with high uncertainty about VBP presence, which, like the isolated high- $z$  municipalities, ought to be targeted by future field searches. Three regions stand out for high uncertainty about VBP presence: northeastern Minas Gerais, central Paraná, and northern Rio Grande do Sul, in Brazil, together with a few municipalities in eastern Paraguay. These are the regions that could contribute most to further improvement of knowledge about the VBP geographic range.

Our estimated VBP range exceeds the area of past Araucaria forest mapped by Hueck (1966) and includes vast areas of the Atlantic forest biome that have been cleared. Nonetheless, both vegetation site covariates—Araucaria and Atlantic forest cover—had strong positive effects on site-occupancy probability. The Paraná Pine plays an important role in the VBP natural history, at least in part of its range, offering roost sites (Prestes et al., 2014), nesting cavities (Cockle et al., 2007) and nutrition during the coldest months of the

year (Collar et al., 2017; Kilpp et al., 2015; Prestes et al., 2014; Tella et al., 2016). Nevertheless, as Araucaria forests only extend as far north as the Campos do Jordão region, parrots from the northern patch must rely on other plant species to obtain whatever resources their southern counterparts get from the Paraná Pine. Living at a lower latitude, they may also escape the harshness of cold winter weeks, when Araucaria seeds are a unique source of energy for several species of the southern fauna (Dénes et al., 2018). Indeed, Carrara et al. (2008) registered foraging and roosting in different trees between northern and southern locations. Likewise, Cockle et al. (2007), as well as Prestes et al. (2014), document foraging and cavity nesting in non-Araucaria Atlantic Forest trees of the southern part of the range. The effect of altitude on site occupancy was smaller and more uncertain than the effects of forest cover, but still indisputably positive. Thus, environmental consequences of altitude are not limiting the VBP distribution.

The increasing availability of citizen-science datasets offers a great opportunity to improve species distribution maps. In our study, eBird, WikiAves and Xeno-canto jointly produced 1.45 times more VBP detections, from samples that covered 45 times more municipalities, than the researcher-led counts. Comparison of the realized geographic range produced by the Full Model (Figure 1b) with equivalent maps produced by separate analysis of each dataset (Figure 2) suggests that the former is more accurate. Even though roost counts had reliable identifications based on the most standardized samples in our data, analysis of roost count data alone produces severe overestimation of occupancy in areas where the species is well known to be absent. Such overestimation, and the high predictive power of the roost count's Model 9, stem from the deliberate sampling bias of roost counting, which is targeted to sites where the species is known to be present. Conversely, Xeno-canto data underestimate occupancy in places where the species was recorded by other datasets. Analysed in isolation, eBird data miss information about the northern part of the VBP distribution; WikiAves, in turn, misses the presence of the species in Paraguay altogether, because it only accepts records from Brazil. The assessment of predictive accuracy enabled us to measure the contribution of each dataset for the final estimates. Excluding one dataset at a time from the analyses, or analysing only one dataset at a time, resulted in worse prediction by the truncated analyses than by the joint analysis of all datasets. Only three out of sixteen possible comparisons resulted in lower deviance for the truncated data; all three corresponding to prediction of roost count or Xeno-canto data, the smallest of the four datasets (Table 2). Exclusion of WikiAves data had the highest impact on predictive power, increasing Deviance for the other datasets between 4% and 25%. WikiAves still lacks an automated data download tool, but it is currently the best source of bird species distribution information in Brazil because of its high coverage and number of records. Xeno-canto has the fewest records and smallest spatial coverage, but it still produced a measurable improvement of predictive power when added to the other datasets. Roost counts and eBird had the least consistent impact on prediction power but still produced an average decrease in deviance across datasets. These two datasets also contributed with sampling replication, essential for

the quantification of false negative results. While there are limits to the usefulness of data integration (Simmonds et al., 2020), in our case, integration clearly improved the fit of models, suggesting that different datasets are capturing similar realities of parrot distribution; otherwise, their combination should make it more, not less difficult to predict excluded data.

Comparisons across datasets were only possible thanks to a methodology that explicitly accounts for differences in data collection among data sources. Model 3 (Tables 2 and S1), which did not account for the variation of detection probability with respect to effort covariates, consistently showed the largest increase in total deviance relative to the Full Model. Exclusion of the occupancy covariates (Model 2) and the spatial autocorrelation component (Model 4) caused an intermediate but measurable decrease in predictive power. The effect of spatial autocorrelation on deviance signals a spatially structured geographic distribution. Such residual structure was evidently not captured by the occupancy covariates in our models. It remains evident after our accounting of environmental factors, either due to endogenous movement of animals between adjacent sites irrespective of the local environment, or due to exogenous environmental factors that are themselves spatially structured and are missing from, or mis-specified in our models (Legendre, 1993). Further interpretation of the spatial structure should clarify the relative importance of endogenous versus exogenous processes, but for now we emphasize that residual structure is still present and should be accounted for in a distribution map of the species. Neglecting spatial contagion easily leads to biased parameter estimates, potentially resulting in erroneous maps (Guélat & Kéry, 2018; Johnson et al., 2013).

The term “citizen science” covers a wide variety of collaborative arrangements that involve people from outside the scientific community in scientific research (Heigl et al., 2019; Tulloch, 2013; Wiggins & Crowston, 2011). When it comes to collaborative recording of wildlife sightings, however, most citizen-science initiatives compile presence-only information from opportunistic samples. Our analysis employs presence-absence (roost counts, eBird) and presence-only (WikiAves, Xeno-canto) data, as well as a planned survey (roost counts) and opportunistic sampling (WikiAves, eBird, Xeno-canto). While integrating planned-survey with opportunistic sampling data, we account for spatial bias in citizen-science data via estimation of effort per sample, based on covariates obtained from the citizen-science datasets themselves. This approach is synthesized in Equations (3) and (4a–c), which express detection probability conditional on species presence. Other studies develop models with more explicit descriptions of the complex variation of sampling effort that is characteristic of citizen-science datasets (e.g. August et al., 2020; Johnston et al., 2021). We opted for a more general approach that, for example, carries no information about individual observer behaviour. There certainly are biases that were not or cannot be accounted for within our approach, especially when analysing one dataset at a time. Nonetheless, our integration of four datasets did increase spatial cover (relative to each dataset) and captured the substantial importance of accounting for spatial

bias in sampling effort. Total deviance more than doubled when effort covariates were removed from the analysis, but it increased only up to 7% (for the eBird data) when we removed the planned-survey roost count data. These results are in agreement with the usefulness of integrating citizen-science with planned-survey data without any particular data source being regarded as a gold standard. They also strengthen our confidence in the contribution of large, multi-species citizen-science datasets for improving knowledge about species distributions.

## ACKNOWLEDGEMENTS

This paper owes a great deal to Reinaldo Guedes who volunteered his free time over the last twelve years to developing and administering WikiAves, the most successful citizen-science initiative in Brazil. Roost counts were supported in large part by *Projeto Charão*, in Brazil, *Proyecto Selva Pino Paraná*, in Argentina, and *Guyra Paraguay*, in Paraguay. Last, but not least, we are indebted to the thousands of bird observers who uploaded photographs, audiorecordings and birding lists to eBird, WikiAves and Xeno-canto.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1111/ddi.13416>.

## DATA AVAILABILITY STATEMENT

The R codes and datasets used for the analyses are openly available at GitHub in the address: <https://github.com/vivuzulian/DataIntegrationModels>.

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## REFERENCES

- Altwegg, R., & Nichols, J. D. (2018). Occupancy models for citizen-science data. *Methods in Ecology and Evolution*, 10(1), 8–21. <https://doi.org/10.1111/2041-210X.13090>
- Araya-Salas, M., & Smith-Vidaurre, G. (2017). warbleR: an R package to streamline analysis of animal acoustic signals. *Methods in Ecology and Evolution*, 8(2), 184–191. <http://dx.doi.org/10.1111/2041-210X.12624>
- August, T., Fox, R., Roy, D. B., & Pocock, M. J. O. (2020). Data-derived metrics describing the behaviour of field-based citizen scientists provide insights for project design and modelling bias. *Scientific Reports*, 10, 11009. <https://doi.org/10.1038/s41598-020-67658-3>
- BirdLife International (2017). *Amazona vinacea*. The IUCN Red List of Threatened Species. <http://dx.doi.org/10.2305/IUCN.UK.2016-3.RLTS.T22686374A93109194.en>
- BirdLife International, & Handbook of the Birds of the World (2016). *Amazona vinacea* (3rd ed.) [Map]. The IUCN Red List of Threatened Species. <http://www.iucnredlist.org>

- Carrara, L. A., Faria, L. C., Matos, J. R., & de Antas, P. T. Z. (2008). Papagaio-de-peito-roxo *Amazona vinacea* (Kuhl) (Aves: Psittacidae) no norte do Espírito Santo: Redescoberta e conservação. *Revista Brasileira de Zoologia*, 25(1), 154–158. <https://doi.org/10.1590/S0101-81752008000100021>
- Cockle, K., Capuzzi, G., Bodrati, A., Clay, R., del Castillo, H., Velázquez, M., Areta, J. I., Fariña, N., & Fariña, R. (2007). Distribution, abundance, and conservation of Vinaceous Amazons (*Amazona vinacea*) in Argentina and Paraguay. *Journal of Field Ornithology*, 78(1), 21–39. <https://doi.org/10.1111/j.1557-9263.2006.00082.x>
- Cockle, K. L., Ibarra, J. T., Altamirano, T. A., & Martin, K. (2019). Interspecific networks of cavity-nesting vertebrates reveal a critical role of broadleaf trees in endangered Araucaria mixed forests of South America. *Biodiversity and Conservation*, 28(12), 3371–3386. <https://doi.org/10.1007/s10531-019-01826-4>
- Collar, N., Boesman, P., & Juana, E. (2017). Vinaceous-breasted Amazon (*Amazona vinacea*). In J. del Hoyo, A. Elliott, J. Sargatal, D. A. Christie, & E. de Juana (Eds.), *Handbook of the birds of the world alive*. Lynx Edicions. <http://www.hbw.com/node/54755>
- Coron, C., Calenge, C., Giraud, C., & Julliard, R. (2018). Bayesian estimation of species relative abundances and habitat preferences using opportunistic data. *Environmental and Ecological Statistics*, 25(1), 71–93. <https://doi.org/10.1007/s10651-018-0398-2>
- Dénes, F. V., Tella, J. L., Zulian, V., Prestes, N. P., Martínez, J., & Hiraldo, F. (2018). Combined impacts of multiple non-native mammals on two life stages of a critically endangered Neotropical tree. *Biological Invasions*, 20, 3055–3068. <https://doi.org/10.1007/s10530-018-1758-4>
- DIVA-GIS (2018). Elevation. Free spatial data. <https://diva-gis.org/gdata>
- Dorazio, R. M. (2014). Accounting for imperfect detection and survey bias in statistical analysis of presence-only data. *Global Ecology and Biogeography*, 23(12), 1472–1484. <https://doi.org/10.1111/geb.12216>
- eBird (2019). *EBird*. An online database of bird distribution and abundance. <https://ebird.org/home>
- Fithian, W., Elith, J., Hastie, T., & Keith, D. A. (2015). Bias correction in species distribution models: Pooling survey and collection data for multiple species. *Methods in Ecology and Evolution*, 6(4), 424–438. <https://doi.org/10.1111/2041-210X.12242>
- Fletcher, R. J., Hefley, T. J., Robertson, E. P., Zuckerman, B., McCreary, R. A., & Dorazio, R. M. (2019). A practical guide for combining data to model species distributions. *Ecology*, 100, e02710.
- Giraud, C., Calenge, C., Coron, C., & Julliard, R. (2016). Capitalizing on opportunistic data for monitoring relative abundances of species. *Biometrics*, 72(2), 649–658. <https://doi.org/10.1111/biom.12431>
- Gregory, R. D., van Strien, A., Vorisek, P., Gmelig Meyling, A. W., Noble, D. G., Foppen, R. P. B., & Gibbons, D. W. (2005). Developing indicators for European birds. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1454), 269–288. <https://doi.org/10.1098/rstb.2004.1602>
- Guélat, J., & Kéry, M. (2018). Effects of spatial autocorrelation and imperfect detection on species distribution models. *Methods in Ecology and Evolution*, 9(6), 1614–1625. <https://doi.org/10.1111/2041-210X.12983>
- Heigl, F., Kieslinger, B., Paul, K. T., Uhlík, J., & Dörler, D. (2019). Opinion: Toward an international definition of citizen science. *Proceedings of the National Academy of Sciences of the United States of America*, 116(17), 8089–8092. <https://doi.org/10.1073/pnas.1903393116>
- Hill, M. O. (2012). Local frequency as a key to interpreting species occurrence data when recording effort is not known. *Methods in Ecology and Evolution*, 3(1), 195–205. <https://doi.org/10.1111/j.2041-210X.2011.00146.x>
- Hooten, M. B., & Hobbs, N. T. (2015). A guide to Bayesian model selection for ecologists. *Ecological Monographs*, 85(1), 3–28. <https://doi.org/10.1890/14-0661.1>
- Hudson, M.-A.-R., Francis, C. M., Campbell, K. J., Downes, C. M., Smith, A. C., & Pardieck, K. L. (2017). The role of the North American Breeding Bird Survey in conservation. *The Condor*, 119(3), 526–545. <https://doi.org/10.1650/CONDOR-17-62.1>
- Hueck, K. (1966). *Die Wälder Südamerikas*. Ökologie, Zusammensetzung un wirtschaftliche Bedeutung.
- Isaac, N. J. B., Jarzyna, M. A., Keil, P., Dambly, L. I., Boersch-Supan, P. H., Browning, E., Freeman, S. N., Golding, N., Guillera-Aroita, G., Henrys, P. A., Jarvis, S., Lahoz-Monfort, J., Pagel, J., Pescott, O. L., Schmucki, R., Simmonds, E. G., & O'Hara, R. B. (2020). Data integration for large-scale models of species distributions. *Trends in Ecology & Evolution*, 35(1), 56–67. <https://doi.org/10.1016/j.tree.2019.08.006>
- Jetz, W., McPherson, J. M., & Guralnick, R. P. (2012). Integrating biodiversity distribution knowledge: Toward a global map of life. *Trends in Ecology & Evolution*, 27(3), 151–159. <https://doi.org/10.1016/j.tree.2011.09.007>
- Johnson, D. S., Conn, P. B., Hooten, M. B., Ray, J. C., & Pond, B. A. (2013). Spatial occupancy models for large datasets. *Ecology*, 94(4), 801–808. <https://doi.org/10.1890/12-0564.1>
- Johnston, A., Hochachka, W. M., Strimas-Mackey, M., Gutierrez, V. R., Robinson, O. J., Miller, E. T., Auer, T., Kelling, S. T., & Fink, D. (2021). Analytical guidelines to increase the value of community science data: An example using eBird data to estimate species distributions. *Diversity and Distributions*, 27(7), 1265–1277. <https://doi.org/10.1111/ddi.13271>
- Kéry, M. (2011). Towards the modelling of true species distributions: Commentary. *Journal of Biogeography*, 38(4), 617–618. <https://doi.org/10.1111/j.1365-2699.2011.02487.x>
- Kéry, M., Gardner, B., & Monnerat, C. (2010). Predicting species distributions from checklist data using site-occupancy models. *Journal of Biogeography*, 37, 1851–1862. <https://doi.org/10.1111/j.1365-2699.2010.02345.x>
- Kilpp, J. C., Prestes, N. P., Pizzol, G. E. D., & Martinez, J. (2015). Dieta alimentar de *Amazona vinacea* no sul e sudeste de Santa Catarina, Brasil. *Atualidades Ornitológicas*, 183, 6.
- La Sorte, F. A., & Somveille, M. (2020). Survey completeness of a global citizen-science database of bird occurrence. *Ecography*, 43, 34–43. <https://doi.org/10.1111/ecog.04632>
- Legendre, P. (1993). Spatial autocorrelation: Trouble or new paradigm? *Ecology*, 74(6), 1659–1673. <https://doi.org/10.2307/1939924>
- Lunn, D. J., Thomas, A., Best, N., & Spiegelhalter, D. (2000). *Statistics and Computing*, 10(4), 325–337. <http://dx.doi.org/10.1023/a:1008929526011>
- Mace, G. M., Collar, N. J., Gaston, K. J., Hilton-Taylor, C., Akçakaya, H. R., Leader-Williams, N., Milner-Gulland, E. J., & Stuart, S. N. (2008). Quantification of extinction risk: IUCN's system for classifying threatened species. *Conservation Biology*, 22(6), 1424–1442. <https://doi.org/10.1111/j.1523-1739.2008.01044.x>
- MacKenzie, D. I., Nichols, J. D., Lachman, G. B., Droege, S., Andrew Royle, J., & Langtimm, C. A. (2002). Estimating site occupancy rates when detection probabilities are less than one. *Ecology*, 83(8), 2248–2255.
- Miller, D. A. W., Pacifici, K., Sanderlin, J. S., & Reich, B. J. (2019). The recent past and promising future for data integration methods to estimate species' distributions. *Methods in Ecology and Evolution*, 10(1), 22–37. <https://doi.org/10.1111/2041-210X.13110>
- Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N., Underwood, E. C., D'Amico, J. A., Itoua, I., Strand, H. E., Morrison, J. C., Loucks, C. J., Allnutt, T. F., Ricketts, T. H., Kura, Y., Lamoreux, J. F., Wettengel, W. W., Hedao, P., & Kassem, K. R. (2001). Terrestrial Ecoregions of the World: A New Map of Life on Earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. *BioScience*, 51(11), 933–938. [http://dx.doi.org/10.1641/0006-3568\(2001\)051\[0933:teotwa\]2.0.co;2](http://dx.doi.org/10.1641/0006-3568(2001)051[0933:teotwa]2.0.co;2)
- Pacifici, K., Reich, B. J., Miller, D. A. W., Gardner, B., Stauffer, G., Singh, S., McKerrow, A., & Collazo, J. A. (2017). Integrating multiple data

- sources in species distribution modeling: A framework for data fusion. *Ecology*, 98(3), 840–850. <https://doi.org/10.1002/ecy.1710>
- Peel, S. L., Hill, N. A., Foster, S. D., Wotherspoon, S. J., Ghiglione, C., & Schiaparelli, S. (2019). Reliable species distributions are obtainable with sparse, patchy and biased data by leveraging over species and data types. *Methods in Ecology and Evolution*, 10(7), 1002–1014. <https://doi.org/10.1111/2041-210X.13196>
- Phillips, S. J., Dudík, M., Elith, J., Graham, C. H., Lehmann, A., Leathwick, J., & Ferrier, S. (2009). Sample selection bias and presence-only distribution models: Implications for background and pseudo-absence data. *Ecological Applications*, 19(1), 181–197. <https://doi.org/10.1890/07-2153.1>
- Prestes, N. P., Martinez, J., Kilpp, J. C., Batistela, T., Turkievicz, A., Rezende, É., & Gaboardi, V. T. R. (2014). Ecologia e conservação de *Amazona vinacea* em áreas simpátricas com *Amazona pretrei*. *Ornithologia*, 6(2), 109–120.
- Rocchini, D., Hortal, J., Lengyel, S., Lobo, J. M., Jiménez-Valverde, A., Ricotta, C., Bacaro, G., & Chiarucci, A. (2011). Accounting for uncertainty when mapping species distributions: The need for maps of ignorance. *Progress in Physical Geography*, 35(2), 211–226. <https://doi.org/10.1177/0309133311399491>
- Simmonds, E. G., Jarvis, S. G., Henrys, P. A., Isaac, N. J. B., & O'Hara, R. B. (2020). Is more data always better? A simulation study of benefits and limitations of integrated distribution models. *Ecography*, 43(10), 1413–1422. <https://doi.org/10.1111/ecog.05146>
- Stauffer, G. E., Miller, D. A. W., Williams, L. M., & Brown, J. (2018). Ruffed grouse population declines after introduction of West Nile virus. *The Journal of Wildlife Management*, 82(1), 165–172. <https://doi.org/10.1002/jwmg.21347>
- Sullivan, B. L., Phillips, T., Dayer, A. A., Wood, C. L., Farnsworth, A., Iliff, M. J., Davies, I. J., Wiggins, A., Fink, D., Hochachka, W. M., Rodewald, A. D., Rosenberg, K. V., Bonney, R., & Kelling, S. (2017). Using open access observational data for conservation action: A case study for birds. *Biological Conservation*, 208, 5–14. <https://doi.org/10.1016/j.biocon.2016.04.031>
- Sullivan, B. L., Wood, C. L., Iliff, M. J., Bonney, R. E., Fink, D., & Kelling, S. (2009). eBird: A citizen-based bird observation network in the biological sciences. *Biological Conservation*, 142(10), 2282–2292. <https://doi.org/10.1016/j.biocon.2009.05.006>
- Tella, J. L., Dénes, F. V., Zulian, V., Prestes, N. P., Martínez, J., Blanco, G., & Hiraldo, F. (2016). Endangered plant-parrot mutualisms: Seed tolerance to predation makes parrots pervasive dispersers of the Parana pine. *Scientific Reports*, 6, 31709. <https://doi.org/10.1038/srep31709>
- Tulloch, A. I. T., Possingham, H. P., Joseph, L. N., Szabo, J., & Martin, T. G. (2013). Realising the full potential of citizen science monitoring programs. *Biological Conservation*, 165, 128–138. <https://doi.org/10.1016/j.biocon.2013.05.025>
- Wiggins, A., & Crowston, K. (2011). From conservation to crowdsourcing: A typology of citizen science. In *2011 44th Hawaii International Conference on System Sciences* (pp. 1–10).
- WikiAves (2019). *WikiAves, a Enciclopédia das Aves do Brasil*. <http://www.wikiaves.com.br>
- Xeno-canto (2019). *Xeno-Canto: Bird Sounds from around the World*. <https://www.xeno-canto.org/>
- Zulian, V., Müller, E. S., Cockle, K. L., Lesterhuis, A., Tomasi Júnior, R., Prestes, N. P., Martinez, J., Kéry, M., & Ferraz, G. (2020). Addressing multiple sources of uncertainty in the estimation of global parrot abundance from roost counts: A case study with the Vinaceous-breasted Parrot (*Amazona vinacea*). *Biological Conservation*, 248, 108672. <https://doi.org/10.1016/j.biocon.2020.108672>

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## SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

**How to cite this article:** Zulian, V., Miller, D. A. W., & Ferraz, G. (2021). Integrating citizen-science and planned-survey data improves species distribution estimates. *Diversity and Distributions*, 00, 1–12. <https://doi.org/10.1111/ddi.13416>

## Supporting Information: Code

**Appendix S1:** R and BUGS code for the Full Model used in estimating the Vinaceous-breasted Parrot geographic range. The code includes the CAR component of the model, accounting for effort, cross-validation and Deviance computation.

```
#Data object specification in R
data <- list(muni1 = datIn$IDENT, muni2 = datOut$IDENT, muni3 = dat2In$IDENT,
            muni4 = dat2Out$IDENT, muni5 = dat3In$IDENT, muni6 =
            dat3Out$IDENT, muni7 = dat4In$IDENT, muni8 = dat4Out$IDENT,
            Y1 = datIn$A_VINACEA, Y3 = dat2In$A_VINACEA, Y5 =
            dat3In$AVINACEA, Y7 = dat4In$A_VINACEA, nMuni = length(muni),
            nObs1 = nrow(datIn), nObs2 = nrow(datOut), nObs3 = nrow(dat2In),
            nObs4 = nrow(dat2Out), nObs5 = nrow(dat3In), nObs6 =
            nrow(dat3Out), nObs7 = nrow(dat4In), nObs8 = nrow(dat4Out),
            TObs = datIn$EFFORT_MIN/60, TObs2 = datOut$EFFORT_MIN/60,
            SSee = dat2In$NSPECIES, SSee2 = dat2Out$NSPECIES, TObs3 =
            dat2In$DURATION.M/60, TObs4 = dat2Out$DURATION.M/60,
            RLen = dat2In$EFFORT.DIS, RLen2 = dat2Out$EFFORT.DIS,
            NPho = dat3In$NPIC, NPho2 = dat3Out$NPIC, NAud = dat3In$NSONG,
            NAud2 = dat3Out$NSONG, NAud3 = dat4In$NSONGS, NAud4 =
            dat4Out$NSONGS, VegCover = VegCover, ArauCover = ArauCover,
            Alt = Altitude, nCell = nrow(hex.centroids), cell.id = cell.id,
            adj = adj, num = num, sumNeigh = sumNeigh)

# Model specification in BUGS language
cat(file = "model.txt", "
model {

    #CAR prior - spatial random effect
    for(j in 1:sumNeigh){weights[j] <- 1}
    spacesigma ~ dunif(0,5)
    spacetau <- 1/(spacesigma*spacesigma)
    delta[1:nCell] ~ car.normal(adj[],weights[],num[],spacetau)

    ###Data model
    for (i in 1:nMuni){ # loop over sites
        mu[i] <- delta[cell.id[i]] + beta[1] + beta[2]*VegCover[i] +
            beta[3]*ArauCover[i] + beta[4]*Alt[i]
        mu.lim[i] <- min(10, max(-10, mu[i]))
        logit(psi[i]) <- mu.lim[i]
        z[i] ~ dbern(psi[i])
    }

    for (n in 1:nObs1){ # loop over observations - Counts - Data In
        e1[n] <- alpha[1]*TObs[n]
        P1[n] <- 1-pow((1-0.5), e1[n])
        zP1[n] <- P1[n]*z[muni1[n]]
        Y1[n] ~ dbern(zP1[n])
    }
}
```



```

for (o in 1:nObs2){      # loop over observations - Counts - Data Out
  e2[o] <- alpha[1]*TObs2[o]
  P2[o] <- 1-pow((1-0.5), e2[o]) # effort model
  zP2[o] <- P2[o]*z[muni2[o]]
  Y2[o] ~ dbern(zP2[o])
}

for (j in 1:nObs3){    # loop over observations - eBird
  e3[j] <- alpha[2]*SSee[j] + alpha[3]*TObs3[j] + alpha[4]*RLen[j]
  P3[j] <- 1-pow((1-0.5), e3[j]) # effort model
  zP3[j] <- P3[j]*z[muni3[j]]
  Y3[j] ~ dbern(zP3[j])
}

for (p in 1:nObs4){   # loop over observations, eBird, Cross-Validation
  e4[p] <- alpha[2]*SSee2[p] + alpha[3]*TObs4[p] + alpha[4]*RLen2[p]
  P4[p] <- 1-pow((1-0.5), e4[p]) #effort model
  zP4[p] <- P4[p]*z[muni4[p]]
  Y4[p] ~ dbern(zP4[p])
}

for (k in 1:nObs5){  # loop over observations - Wikiaves
  e5[k] <- alpha[5]*NPho[k] + alpha[6]*NAud[k]
  P5[k] <- 1-pow((1-0.5), e5[k]) #effort model
  zP5[k] <- P5[k]*z[muni5[k]]
  Y5[k] ~ dbern(zP5[k])
}

for (s in 1:nObs6){  #loop over observations - Wikiaves - Cross-Validation
  e6[s] <- alpha[5]*NPho2[s] + alpha[6]*NAud2[s]
  P6[s] <- 1-pow((1-0.5), e6[s]) #effort model
  zP6[s] <- P6[s]*z[muni6[s]]
  Y6[s] ~ dbern(zP6[s])
}

for (h in 1:nObs7){  #loop over observations - Xeno-Canto data
  e7[h] <- alpha[7]*NAud3[h]
  P7[h] <- 1-pow((1-0.5), e7[h]) #effort model
  zP7[h] <- P7[h]*z[muni7[h]]
  Y7[h] ~ dbern(zP7[h])
}

for (t in 1:nObs8){  # loop over obsvts - Xeno-canto - Cross-Validation
  e8[t] <- alpha[7]*NAud4[t]
  P8[t] <- 1-pow((1-0.5), e8[t]) #effort model
  zP8[t] <- P8[t]*z[muni8[t]]
  Y8[t] ~ dbern(zP8[t])
}

#Priors for betas - psi
beta[1] ~ dunif(-10,10)
beta[2] ~ dunif(-10,10)
beta[3] ~ dunif(-10,10)

```

```

beta[4] ~ dunif(-10,10)

#Priors for alphas - effort model
for (b in 1:7){
  alpha[b] ~ dnorm(0,0.0001)I(0,10000)
}

#compute the mean detection probability of each dataset:
muP1 <- mean(P1[])
muP2 <- mean(P2[])
muP3 <- mean(P3[])
muP4 <- mean(P4[])
muP5 <- mean(P5[])
muP6 <- mean(P6[])
muP7 <- mean(P7[])
muP8 <- mean(P8[])

}
")

#Back to R language:

#Specification of Initial Values
inits = function() {list(z = rep(1, data4$nMuni))}
params <- c("beta", "psi", "z", "alpha", "muP1", "muP2", "muP3", "muP4",
           "muP5", "muP6", "muP7", "muP8", "Y2", "Y4", "Y6", "Y8",
           "spacesigma", "delta")

#MCMC settings
nc <- 3;  nb <- 150000;  ni <- 200000;  nt <- 100

out <- bugs(data = data, inits = inits, parameters.to.save = params,
           model.file = "model.txt", n.chains = nc, n.iter = ni,
           n.burnin = nb, n.thin = nthin, debug = TRUE)

#Deviance calculation based on the model output
likelihood2 <- (out$mean$Y2^datOut$A_VINACEA)*((1- out$mean$Y2)^
           (1-datOut$A_VINACEA)) #likelihood
DEV2 <- -(2*(sum(log(likelihood2))))

likelihood4 <- (out$mean$Y4^ dat2Out$A_VINACEA)*((1- out$mean$Y4)^
           (1- dat2Out$A_VINACEA)) #likelihood
DEV4 <- -(2*(sum(log(likelihood4))))

likelihood6 <- (out$mean$Y6^ dat3Out$AVINACEA)*((1- out$mean$Y6)^
           (1- dat3Out$AVINACEA)) #likelihood
DEV6 <- -(2*(sum(log(likelihood6))))

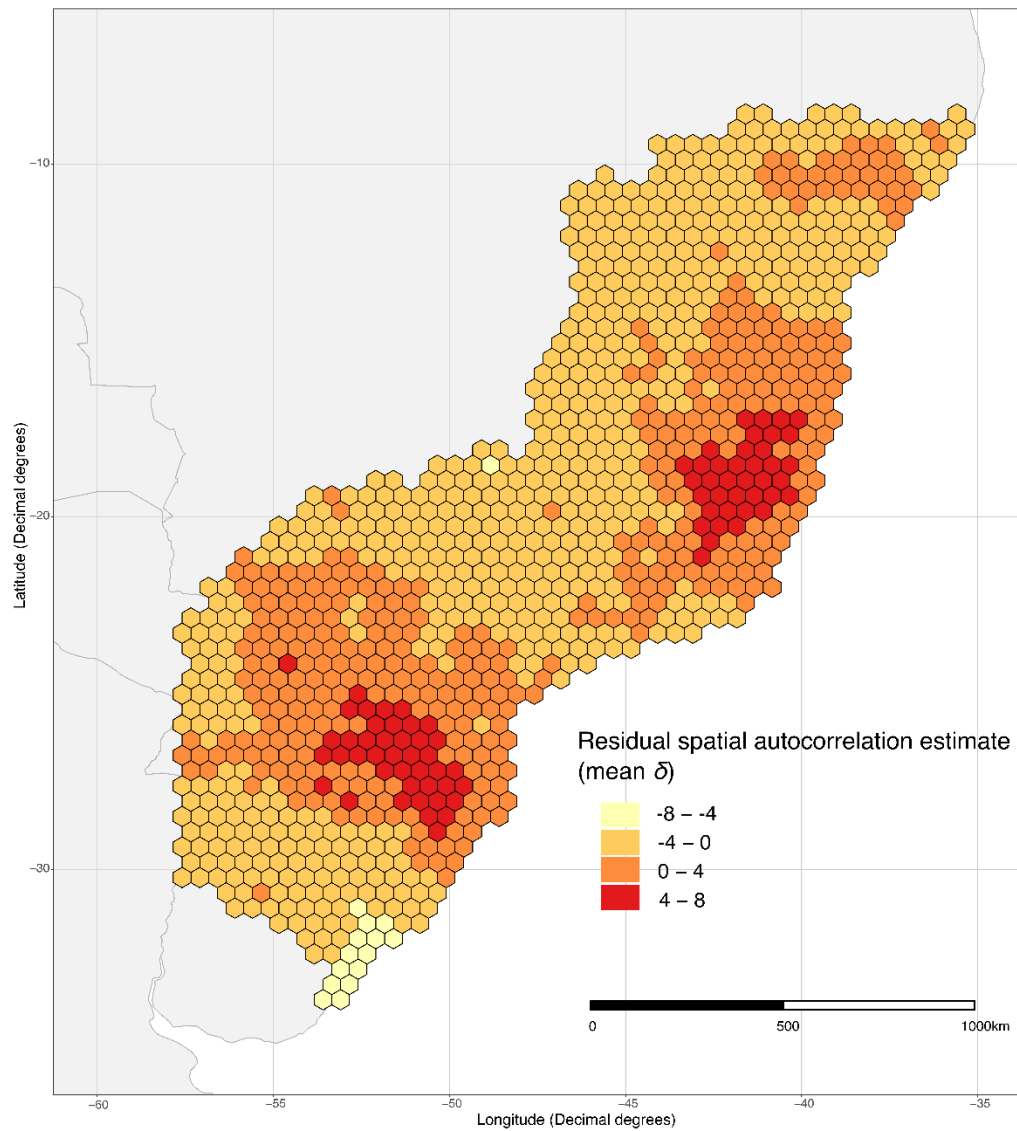
likelihood8 <- (out$mean$Y8^ dat4Out$A_VINACEA)*((1- out$mean$Y8)^
           (1- dat4Out$A_VINACEA)) #likelihood
DEV8 <- -(2*(sum(log(likelihood8))))

DEVtotal <- DEV2 + DEV4 + DEV6 + DEV8 #total deviance

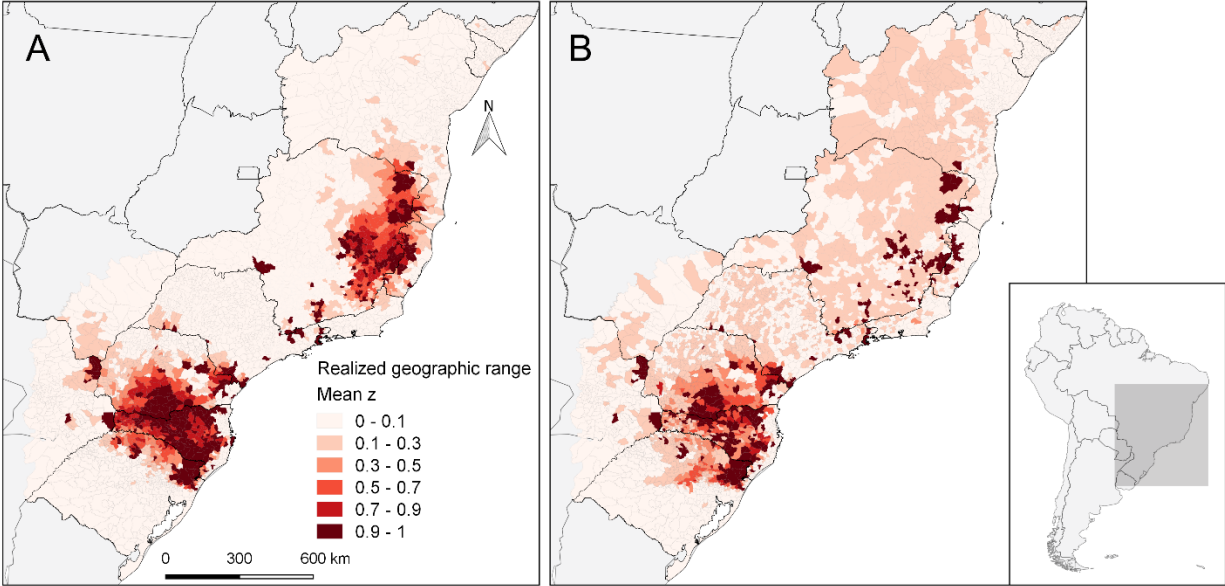
```

## Supporting Information: Figures

**Figure S1:** Residual spatial autocorrelation estimated by the Full Model. Dark red hexagons represent highly positive spatial autocorrelation, i.e. strong clustering of occupancy not explained by environmental covariates.



**Figure S2:** Comparison between the realized geographic range (mean z) according to the Full Model (A) and according to the model without the spatial component (B).



## Supporting Information: Tables

**Table S1:** Results of two additional cross-validation trials performed with the first four models in the study. Model 1, the ‘Full Model’, includes spatial autocorrelation plus detection as well as occupancy covariates. It was fitted to data from all datasets: roost counts (RC), eBird (EB), WikiAves (WA), and Xeno-canto (XC). Model 2 equals model 1 without spatial autocorrelation. Models 3 and 4 are variants of model 1 without, respectively, detection and occupancy covariates. In these two trials, as well as in that reported in Table 2 of the manuscript, the Full Model always has the lowest, and the model with no detection covariates always has the highest total deviance. The ranking of models 1-4 with respect to specific datasets changes between trials but the full model is still the model that most frequently has the lowest deviance, while model 3 (no detection covs.) most frequently has the highest. Each trial below corresponds to one random exclusion of 20% of the data, followed by model fitting, parameter estimation, prediction of the excluded data and computation of deviance.

| Trial 1               |                | Deviance in each data set |               |               |             |
|-----------------------|----------------|---------------------------|---------------|---------------|-------------|
| Models                | Total Deviance | RC                        | EB            | WA            | XC          |
| <b>1. Full Model</b>  | <b>1099.70</b> | <b>94.73</b>              | <b>846.84</b> | <b>148.57</b> | <b>9.55</b> |
| 2. No CAR             | 1205.34        | 139.25                    | 888.54        | 168.69        | 8.84        |
| 3. No detection covs. | 1529.71        | 227.97                    | 1123.03       | 156.54        | 22.14       |
| 4. No occupancy covs. | 1365.83        | 140.16                    | 1040.62       | 170.56        | 14.48       |

| Trial 2               |                | Deviance in each data set |               |               |              |
|-----------------------|----------------|---------------------------|---------------|---------------|--------------|
| Models                | Total Deviance | RC                        | EB            | WA            | XC           |
| <b>1. Full Model</b>  | <b>921.62</b>  | <b>197.06</b>             | <b>507.49</b> | <b>190.64</b> | <b>26.41</b> |
| 2. No CAR             | 1173.45        | 308.87                    | 604.57        | 228.83        | 31.17        |
| 3. No detection covs. | 1755.89        | 548.99                    | 960.81        | 204.11        | 41.98        |
| 4. No occupancy covs. | 955.55         | 245.01                    | 492.30        | 190.31        | 27.91        |

**7. CAPÍTULO 3: Endemic and threatened *Amazona* parrots of the Atlantic Forest: an overview of their geographic range and population size**

Artigo publicado na revista *Diversity*.

Article

# Endemic and Threatened *Amazona* Parrots of the Atlantic Forest: An Overview of Their Geographic Range and Population Size

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**Abstract:** *Amazona* is the largest genus of the Psittacidae, one of the most threatened bird families. Here, we study four species of *Amazona* (*Amazona brasiliensis*, *A. pretrei*, *A. vinacea*, and *A. rhodocorytha*) that are dependent on a highly vulnerable biome: the Brazilian Atlantic Forest. To examine their distribution and abundance, we compile abundance estimates and counts, and develop site-occupancy models of their geographic range. These models integrate data from formal research and citizen science platforms to estimate probabilistic maps of the species' occurrence throughout their range. Estimated range areas varied from 15,000 km<sup>2</sup> for *A. brasiliensis* to more than 400,000 km<sup>2</sup> for *A. vinacea*. While *A. vinacea* is the only species with a statistical estimate of abundance (~8000 individuals), *A. pretrei* has the longest time series of roost counts, and *A. rhodocorytha* has the least information about population size. The highest number of individuals counted in one year was for *A. pretrei* (~20,000), followed by *A. brasiliensis* (~9000). Continued modeling of research and citizen science data, matched with collaborative designed surveys that count parrots at their non-breeding roosts, are essential for an appropriate assessment of the species' status, as well as for examining the outcome of conservation actions.

**Keywords:** *Amazona*; Psittacidae; species distribution models; data integration models; occupancy models; citizen-science; population size; count data

**Citation:** Zulian, V.; Miller, D.A.W.; Ferraz, G. Endemic and Threatened *Amazona* Parrots of the Atlantic Forest: An Overview of Their Geographic Range and Population Size. *Diversity* **2021**, *13*, 416. <https://doi.org/10.3390/d13090416>

Academic Editor: Juan Carlos Illera

Received: 4 June 2021

Accepted: 23 August 2021

Published: 30 August 2021

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## 1. Introduction

Three hundred and ninety-five species of parrots, macaws, and parakeets constitute the Psittacidae family, the largest non-passerine bird family in the world [1]. With 27% (108) of its species threatened with extinction [1], the Psittacidae is the bird family with the highest absolute number of threatened species, that is, species classified as 'vulnerable', 'endangered', 'critically endangered', or 'extinct in the wild', by the International Union for Conservation of Nature and Natural Resources (IUCN). In proportional terms, the Psittacidae come only after the much smaller families of albatrosses and cranes with, respectively, 68% and 66% of their species threatened. Habitat loss and nest poaching are two key factors endangering Psittacidae populations [2,3]. Being dependent on forest habitats, most Psittacidae species require natural cavities to nest [3] and are thus directly impacted by forest clearance [2] and selective logging [4], caused primarily by agro-industrial expansion [5,6]. Nest poaching disproportionately affects species that are colorful, with large body size, relative ease of capture, and that sell for the highest prices [7,8].

The most diverse genus among the Psittacidae is the neotropical genus *Amazona*, or Amazon parrots, with 36 species distributed from northern Argentina to northern Mexico [1]. One half (18) of the *Amazona* species are globally threatened, and 25 species have decreasing population sizes, according to the IUCN Red List [1]. Nest poaching has been

reported by Wright et al. [8] as the main cause of mortality in four species: *A. vinacea*, *A. kawalli*, *A. ochrocephala*, and *A. auropalliata*. Habitat loss is also a threat to the genus, especially in those biomes that have been more subjected to deforestation, such as the Atlantic Forest of Brazil. Home to seven *Amazona* species [9], the Atlantic Forest is the second largest rainforest in South America [10,11] and is a global biodiversity hotspot [12]. The biome has lost almost 90% of its forest cover since the onset of European colonization [12], and only 1% of its original extent is presently included in protected areas [10]. According to one projection to 2070 [13], the Atlantic Forest region will lose bird habitat at the rate of 1.2% to 3.3% per decade—the highest rate of loss estimated by that study for any region of the world. Realizing the potential impact of land use in the Atlantic Forest on parrot populations [14], as well as the relative importance of the genus *Amazona* among the Psittacidae, we direct our attention here to what we consider to be the most emblematic *Amazona* species of the Atlantic Forest biome: *A. brasiliensis*, *A. rhodocorytha*, *A. vinacea*, and *A. pretrei*. They are endemic to the Atlantic Forest [15] and classified by the IUCN, respectively, as Near-Threatened, Vulnerable, Endangered, and Vulnerable.

Geographic range and population size are two key descriptors of the state of any living species. Since their temporal trajectories offer evidence of population trends, these two variables inform four out of the five criteria used by the IUCN in assigning species to threat categories [16]. Notwithstanding, the IUCN Red List profiles of these four species in this study reveal substantial uncertainty about their geographic ranges and limited information about how the estimated population sizes were obtained. Our goal here is to fill this knowledge gap to the extent that is possible by compiling information from the ornithological literature and citizen-science platforms. We review information on population sizes based on published abundance estimates and counts of all species. To address geographic ranges, we draw new maps for the four species. Our maps express the species' distribution as occupancy probability per municipality. The statistical models used for producing the new maps integrate data from three different citizen-science platforms (eBird, Wikiaves, and Xeno-Canto) as well as from formal research databases, where available. We hope that improved knowledge about abundance and distribution of *Amazona* species in the Atlantic Forest will help direct future monitoring and conservation efforts, as well as strengthen the basis for threat assessments.

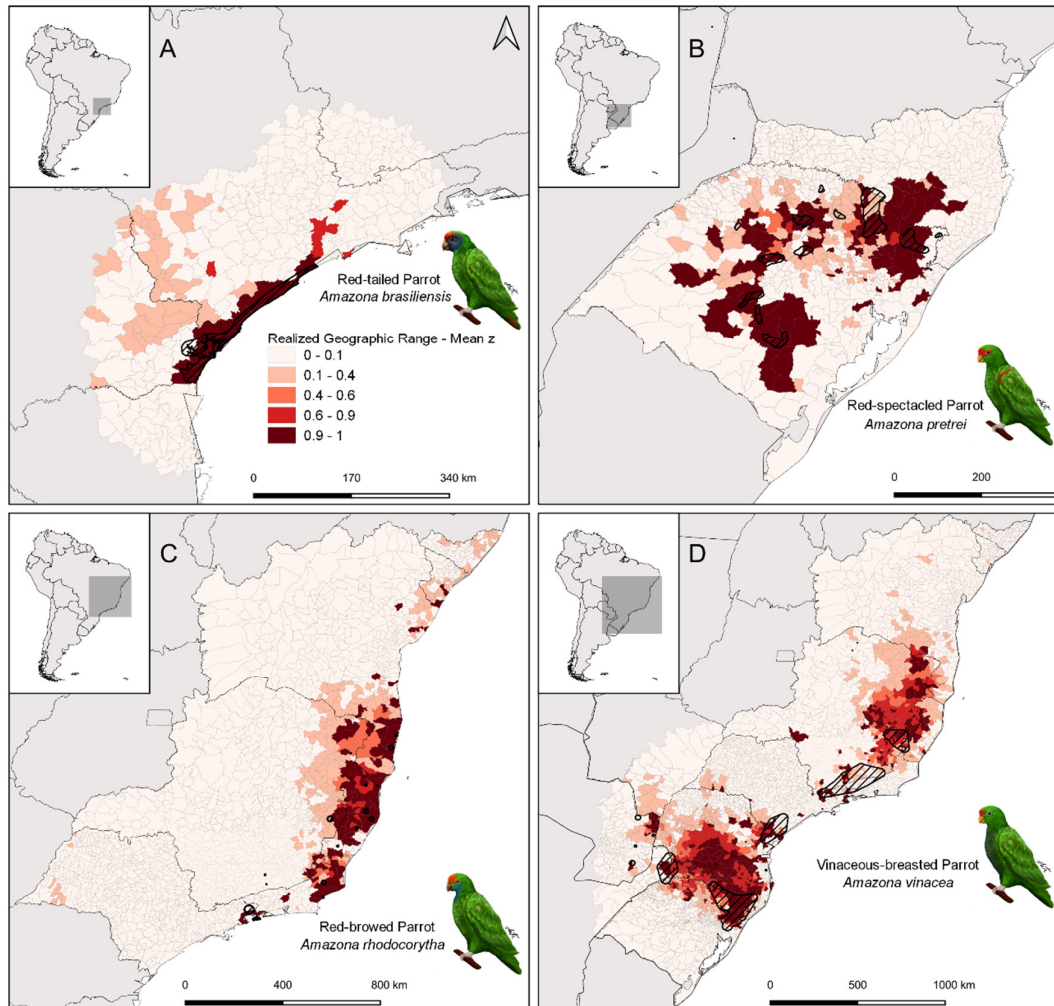
## 2. Materials and Methods

### 2.1. Study Area and Data Collection

We organized information about the population size and the geographic range of *Amazona brasiliensis*, *A. pretrei*, *A. rhodocorytha*, and *A. vinacea* following two different approaches. For population size, we compiled all the information about counts or abundance estimates that we could find for each species, including results from peer-reviewed papers, reports, books, and academic theses (Supplementary Tables S1–S3). Count data were collected by four different research teams, during scientific research or monitoring programs. The counts were performed at regularly used roosts or near points of frequent flyover by parrots, at dawn and dusk. For geographic range mapping, we compiled detection–non-detection data from citizen-science platforms and research project databases. Such data were analyzed separately for each species, with a site-occupancy, data-integration model following Zúlian, Miller, and Ferraz [17]. We varied the geographic extent, or focal area, used to fit each species' model (Figure 1). Focal areas included either all the states or provinces where the species were detected (*A. rhodocorytha* and *A. vinacea*) or all the municipalities within 150 km of the closest detection (*A. brasiliensis* and *A. pretrei*). These areas ranged from a little over 160,000 km<sup>2</sup>, for *A. brasiliensis*, to more than 1.5 million km<sup>2</sup>, in the case of *A. vinacea* (Figure 1). We are confident that the extent for each species covers the entirety of each species' potential area of occurrence. The *A. vinacea* range map that we present here is the only map in this paper that combines formal research and citizen-science data. This map is identical to that shown



by Zulian, Miller, and Ferraz [17], in a study focused on devising optimal methods for fitting distribution models to multiple data streams, which informs the approach that we used here. Geographic range analyses for the other three species are based uniquely on citizen-science data, as explained below.



**Figure 1.** Geographic ranges of the four study species represented by the mean of the true occupancy state ( $z$ ) estimated for each municipality. Intermediate values—of  $z \sim 0.5$ —indicate the highest uncertainty about occupancy by each species. Black dashed polygons are the Extant range of each species according to the IUCN Red List of Threatened Species [1].

We obtained records of *A. vinacea*, *A. brasiliensis*, *A. rhodocorytha*, and *A. pretrei* from citizen-science platforms eBird [18], WikiAves [19], and Xeno-canto [20], corresponding to the period between 1 January 2008 and 31 December 2018. For *A. vinacea*, we also included a formal research dataset derived from roost counts and described by Zulian et al. [21]. Our sampling unit is the municipality, where the number varied from 3701 to 405 depending on the species. Citizen-science platforms store data resulting from field visits with highly variable duration, distance covered, observation technique, and observer experience. This lack of standardization requires platform-specific data processing solutions. In particular, eBird data come in the form of checklists, which contain information about observation effort per list. The number of lists per municipality varied from 1 to 3245, with a mean of 33 lists, collected at different times of the year by different observers. WikiAves and Xeno-canto, on the other hand, gather records for a municipality in the form of individual species observations that are not aggregated in any form of

observation ‘session’ per municipality and observer. As a result, we have the equivalent of replicate visits for eBird, but not for the other two platforms, where each municipality has only one ‘visit’.

Data processing consisted of some filtering, formatting data matrices, and obtaining effort covariates for all platforms. Starting with eBird, we excluded incomplete checklists, checklists without location information, and checklists that potentially spanned more than one municipality due to long distance (>12 km) or long time traveled (>360 min). We set up a matrix of detection–non-detection histories based on eBird data for each parrot species. In this matrix, municipalities appeared in rows and consecutive checklists of each municipality in columns. Matrix elements were ‘1’, for municipalities and checklists where the parrot species were detected, or ‘0’ where not detected. We calculated three covariates of sampling effort for each eBird checklist and municipality: the total number of species recorded, the number of minutes spent observing, and the number of kilometers traveled. For WikiAves and Xeno-canto, data filtering consisted of deleting sightings of individuals reported as escaped from captivity. Since WikiAves receives photographic and audio records of species, we organized data into two vectors per parrot species, one for the number of photographs and one for the number of audio recordings of that species in each unique municipality. For the WikiAves data, we calculated two covariates of effort: the number of photos and the number of audio recordings of all species, per municipality. Finally, the Xeno-canto platform hosts only audio recordings of bird sounds, so its detection data were easily organized into a single vector per parrot species, holding that species’ number of audio recordings per municipality. We also collected the total number of recordings of any species uploaded for each municipality for use as a covariate of Xeno-canto sampling effort. For the *A. vinacea* research data, we created a detection–non-detection matrix with municipalities as rows and counts as columns. Matrix cells corresponding to counts with at least one parrot received a detection (‘1’), and those with no parrots received a non-detection (‘0’). Here, we used the count’s duration, in minutes, as a covariate of sampling effort (see Zulian, Miller, and Ferraz [17] for details).

## 2.2. Data Analysis

We drew range maps representing the estimated probability of site (or municipality) occupancy by each species during the eleven-year study period. We follow a static approach as originally described by MacKenzie et al. [22] and define ‘occupancy’ as the probability that a site was occupied by the given species at any point during the whole eleven-year study period. One of the species—*A. pretrei*—is known for its within-year shifts in distribution, which result in exceptionally large concentrations of individuals during the non-breeding season. Therefore, for this species alone, we estimated both the full-year distribution for the species and seasonal range maps. Seasonal distributions were obtained with the same modeling approach applied to four non-overlapping temporal subsets of the data, each corresponding to one trimester of the year and including information from all years. At the core of our statistical approach to site occupancy, there is a process model of the true occupancy state,  $z_i$ , of each municipality,  $i$ , which takes the value of ‘1’ for those municipalities that are occupied by the species of interest, and ‘0’ for those that are not. This state follows a Bernoulli distribution with a mean  $\psi_i$ :

$$z_i \sim \text{Bernoulli}(\psi_i). \quad (1)$$

The occupancy probability in each municipality  $i$ ,  $\psi_i$ , varies according to  $n$  environmental covariates,  $X_{n,i}$ , according to a generalized linear model with a logit link function. Since the four species of parrots are associated with Atlantic Forest and altitude [23–25], we included the Atlantic Forest cover and average altitude as covariates of municipality  $i$  occupancy. We also included the Araucaria Forest cover as a covariate of occupancy by *A. pretrei* and *A. vinacea*, since they rely heavily on Araucaria seeds for food during the winter [23,26,27], and a Dense Forest cover as a covariate of occupancy by *A. brasiliensis*, because this species is apparently associated with dense, lowland coastal forest

[25,28,29]. We obtained Atlantic Forest cover data from Ribeiro et al. (in prep.), and Dense Forest cover data from the Brazilian Instituto Brasileiro de Geografia e Estatística (<https://www.ibge.gov.br/> (accessed on 30 June 2021)) [30]. Average municipality altitude,  $x$ , in meters, is from DIVA-GIS (<https://www.diva-gis.org/> (accessed on 18 November 2019)) [31], log-transformed as  $\log(x + 1)$ . Our linear model of occupancy also included a spatial random effect to account for unexplained spatial autocorrelated variation ( $\delta_i$ ):

$$\text{logit}(\psi_i) = \beta_0 + \beta_1 * X_{1,i} + \beta_2 * X_{2,i} + \dots + \delta_i. \quad (2)$$

In this model, occupancy covariates measured at municipality  $i$  are given by  $X_{1,i}$ ,  $X_{2,i}$ , ..., and  $\beta_0$ ,  $\beta_1$ ,  $\beta_2$ , ... are estimated coefficients. The spatial component of our model follows a conditional auto-regressive (CAR) distribution [17] and was used to estimate correlated spatial variation in the data that is not explained by our covariates. To avoid confounding effects of municipality size variability and to gain replication within spatial units in the CAR analysis, we represented the spatial random effect using a hexagonal lattice overlaid on the study area, with municipalities assigned to the lattice cell that matches their centroid. Hexagonal cells measured  $0.5^\circ$  latitude across, and all the first-order neighbors of each cell were given a weight of 1 when fitting the CAR model.

Ours is a data-integration approach because it models detections from different databases with a joint-likelihood that shares the same occupancy process described above [32,33], for each parrot species. Within each database, detection was expressed as a conditional probability,  $p_j^*$ , of detecting the species as a function of an estimated amount of sampling effort,  $E_j$ , for visit  $j$  [17,33,34]:

$$p_j^* = 1 - (1 - p)^{E_j}, \quad (3)$$

where  $p$  is the probability of detection per unit of effort. Since we are using indirect, and sometimes several metrics of effort for each data source (our effort covariates), we estimated the parameter  $E_j$  for each sample  $j$  as a linear function of the covariates. Thus, for each dataset,  $DS_n$ , with  $n$  varying between one and four (roost counts, eBird, WikiAves, and Xeno-canto), we have:

$$E_j^{DS_n} = \alpha_1 * X1_j + \alpha_2 * X2_j + \alpha_3 * X3_j, \quad (4)$$

were  $X1_j$ ,  $X2_j$ , and  $X3_j$  are effort covariates measured on visit  $j$ . We used one to three covariates depending on data type. We fixed  $p$  at a value of 0.5, so that the  $\alpha_1$ – $\alpha_3$  coefficients express the relationship between covariates and the effort necessary to reach a detection probability of 0.5 per unit of effort. Without fixing  $p$ , Equation (3) becomes over-parameterized. Having modeled a conditional probability of detection,  $p_j^*$ , we can represent the detection–non-detection data,  $Y_{ij}$ , as the outcome of a Bernoulli distribution, that accounts for the true state of each municipality,  $z_i$ , and the conditional probability of detection, as follows:

$$Y_{ij} \sim \text{Bernoulli}(z_i \times p_j^*). \quad (5)$$

We fitted all the models using a Bayesian estimator coded in the BUGS language and implemented on WinBugs software [35]. Inference was based on draws from the posterior distribution of model parameters using a Markov Chain Monte Carlo (MCMC) algorithm with three chains, 200,000 iterations, and a burn-in phase of 150,000 (see code in Supplementary S1 in the Supplementary Materials). All results presented here correspond to chains that converged to an R-hat lower than 1.1. We draw maps of ‘realized occupancy’ given by the mean of the estimated  $z_i$  for each municipality and estimated the area of each species’ geographic range as the sum of all municipality areas weighted by each municipality’s predicted occupancy,  $\psi_i$ , estimate.

### 3. Results

We used a total of 100,289 samples, collected across 3701 municipalities, to inform the estimation of geographic ranges of the four parrot species that we studied. The datasets showed a wide coverage, with more than 90% of the municipalities in each species' study area having at least one sample (Table 1). Alone, the *A. vinacea* dataset accounted for almost 50% of the samples and 58% of the detections, while *A. pretrei* had the smallest dataset, with 18% of the samples and 10% of the detections (Table 1). *A. brasiliensis* had the third highest number of samples, but only 15 municipalities with at least 1 detection. *A. rhodocorytha* had the second smallest sample size, but the second largest number of detections (Table 1).

Our estimated geographic ranges differed from the Extant area calculated from the range maps reported by the IUCN for all four species (Table 1). *A. vinacea* had the largest estimated range, encompassing more than 400,000 square kilometers [17], followed by *A. rhodocorytha*, with approximately 134,000 square kilometers (Figure 1). The discrepancies between the IUCN Extant area and our estimates are not negligible: while our geographic range estimate is three times larger than the IUCN value for *A. vinacea*, it is six times larger for *A. pretrei*. The biggest discrepancy is for *A. rhodocorytha*, for whom the IUCN reports a range 50 times smaller than our estimate. Geographic ranges are an outcome of history and environmental constraints. Our results show how the environmental covariates of Atlantic Forest cover, Araucaria Forest cover, and Altitude help explain the distribution of *A. vinacea*, with all three having strong and positive effects on site-occupancy probability (Table 2). Based on our models, species' detection data, and environmental covariate information, there is no evidence of other statistically distinguishable effects of environmental factors on site occupancy by any of the four species of parrots (i.e., the 95% credible intervals of other coefficients in Table 2 are nearly centered on zero).

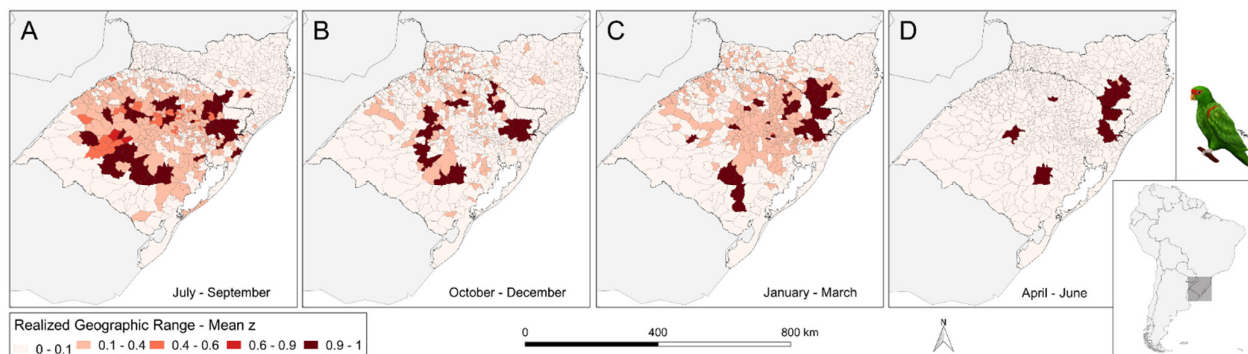
**Table 1.** Sample size, spatial coverage, and number of detections for the four parrot species. Sample size is the number of samples collected from the citizen-science and research datasets, as defined in the text. Coverage is the proportion of municipalities in each study area with at least one sample. The labels  $n_{det}$  and  $n_{muni}$  show, respectively, the number of parrot detections and the number of municipalities with at least one detection. The last two columns show geographic ranges sizes: the IUCN Extant area is given in each species' online entry to the IUCN Red List of Threatened Species. The estimated geographic range is the sum of municipality areas weighted by the estimated probability the species occurred in each municipality (given here by the mean  $\pm$  standard deviation of the a posteriori distribution of range size, followed by its 95% credible interval (in parentheses)).

| Species   | Sample Size | Coverage % | $n_{det}$ | $n_{muni}$ | IUCN Extant Area (km <sup>2</sup> ) | Estimated Geographic Range (km <sup>2</sup> ) |
|---|-------------|------------|-----------|------------|-------------------------------------|---|
| <i>Amazona brasiliensis</i><br>(Red-tailed Parrot)    | 16,705      | 99.7       | 192       | 15         | 4750                                | 15,627 $\pm$ 8843<br>(3127–31,414)            |
| <i>Amazona pretrei</i><br>(Red-spectacled Parrot)     | 5477        | 92.7       | 187       | 73         | 10,430                              | 66,203 $\pm$ 11,425<br>(45,727–90,367)        |
| <i>Amazona rhodocorytha</i><br>(Red-browed Parrot)    | 30,867      | 94.2       | 346       | 86         | 2672                                | 134,355 $\pm$ 13,922<br>(109,288–162,828)     |
| <i>Amazona vinacea</i><br>(Vinaceous-breasted Parrot) | 47,240      | 91.9       | 1007      | 339        | 145,700                             | 434,670 $\pm$ 28,911<br>(382,887–496,550)     |

**Table 2.** Coefficients of the occupancy equation in each species model. The numbers show the mean  $\pm$  standard deviation and 95% credible intervals (in parentheses) of the a posteriori distribution of each parameter.

| Species                     | Atlantic Forest                  | Dense Forest                     | Araucaria Forest                | Altitude                         |
|-----------------------------|----------------------------------|----------------------------------|---------------------------------|----------------------------------|
| <i>Amazona brasiliensis</i> | $-0.63 \pm 2.23$<br>(-5.39–3.48) | $-1.33 \pm 3.14$<br>(-7.71–4.77) | —                               | $0.23 \pm 0.44$<br>(-0.72–0.94)  |
| <i>Amazona pretrei</i>      | $-0.55 \pm 1.08$<br>(-2.70–1.56) | —                                | $0.47 \pm 1.05$<br>(-1.55–2.53) | $0.15 \pm 0.18$<br>(-0.21–0.52)  |
| <i>Amazona rhodocorytha</i> | $0.84 \pm 0.91$<br>(-1.70–1.84)  | —                                | —                               | $-0.14 \pm 0.20$<br>(-0.51–0.25) |
| <i>Amazona vinacea</i>      | $2.11 \pm 0.86$<br>(0.37–3.79)   | —                                | $2.13 \pm 0.98$<br>(0.29–4.10)  | $0.85 \pm 0.12$<br>(0.58–1.05)   |

The subdivision of *A. pretrei* data into trimesters generates four substantially different geographic range maps (Figure 2). During the early breeding season months of July to September, the species is at its most dispersed (Figure 2A). During this period, 39 municipalities throughout the focal area have realized occupancy greater than 0.9 (i.e., mean  $z > 0.9$ ), even though almost all of them are in the state of Rio Grande do Sul. During the Fall months of April to June, however, *A. pretrei* individuals appear aggregated in only 12 municipalities that have realized occupancy greater than 0.9 (Figure 2D). These municipalities form four disjunct clusters in the Rio Grande do Sul and Santa Catarina states. The transition from the aggregated to the dispersed state is faster than the transition from dispersed to aggregated, which takes place from October to March and is represented by the intermediate ranges in panels B and C, of Figure 2.

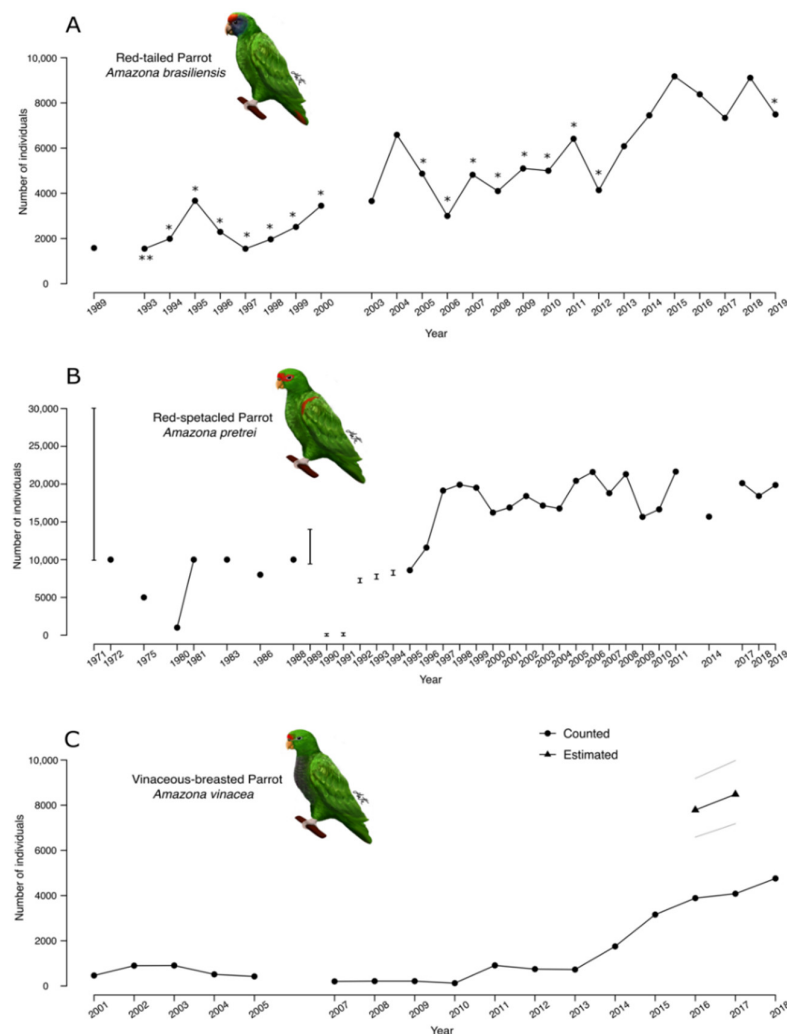


**Figure 2.** Seasonal variation of the geographic range of the Red-Spectacled Parrot (*Amazona pretrei*) as shown by the mean of the true occupancy state ( $z$ ) estimated for each municipality. Each panel represents a trimester, the sequence starting with July–September (A), when the species is most dispersed, and proceeds in three-month intervals to October–December (B), January–March (C) until April–June (D), when it aggregates in only a few municipalities. Darker tones of red indicate higher mean  $z$ ; intermediate tones indicate the highest uncertainty about species presence.

There is much less information about the abundance of Atlantic Forest *Amazona* species than about their geographic range. The species for which we could assemble the longest time series of roost counts was *A. pretrei*, which has a long-term monitoring program led by the same team of researchers since the mid-1990s (Figure 3B). *A. pretrei* is also the species with highest counted number of individuals. Its earliest counts, performed in 1971 by Forshaw and Cooper (ref [36] cited by [37]), returned between 10,000 and 30,000 individuals (Figure 3B). Later, during the 1970s and 1980s, Belton [38] and Varty et al. [37] reported a decline in the number of individuals counted, with recovery during the 1990s. Since 1997, the yearly sum of *A. pretrei* counts has varied around 20,000 individuals (Figure 3B) [39–42]. The second longest time series of roost counts is that of *A. brasiliensis*. This species also has an ongoing monitoring program, coordinated by the same team throughout the last two decades [43]. The sum of *A. brasiliensis* counts has varied, always

below 10,000 individuals, over the last three decades [28,29,43–61]. Figure 3A shows a tendency towards increasing counts, but one should not rush to interpret this as evidence of population growth because the count reports do not incorporate corrections for variation in effort through time. *A. vinacea* has the shortest time series of roost counts [21,27,42,62–64] (Figure 3C) but is the only species with a published statistical estimate of population size, which does account for temporal changes in sampling effort, as well as for detection errors [21]. There are two estimates, for the non-breeding seasons of 2016 and 2017, both in the vicinity of 8500 individuals and with 95% credible intervals entirely below the 10,000-individual mark.

We could not assemble a time series of *A. rhodocorytha* counts, as the few published count results were obtained in sparse locations that were not revisited in different years. In 1998, Marsden et al. [65] searched for the species in two separate sites covering 427 km<sup>2</sup> of Bahia and Espírito Santo states, reporting distance-sampling estimates of, respectively, 238 ± 174 and 5990 ± 1680 (mean ± standard error) individuals. Later, in 2008, Klemann-Júnior et al. [66] counted 2295 individuals for all of Espírito Santo state. The *Plano de Ação Nacional para a Conservação dos Papagaios da Mata Atlântica* considers that the *A. rhodocorytha* population size is around 10,000 individuals, based on expert opinion [41], but no more demographic information is available.



**Figure 3.** Number of Red-Tailed (A), Red-Spectacled (B), and Vinaceous-Breasted (C) Parrots counted by research teams throughout the last fifty years. Panel (C) also includes two estimates of

the Vinaceous-Breasted Parrot population size, with gray lines showing bounds of the 95% credible interval of the a posteriori distribution of population size. These are the only statistical estimates of population size available in the literature for any of the study species. There is no plot for the Red-Browed Parrot because we could not find published records of count results for this species. Some of the Red-Spectacled Parrot counts were reported as intervals and appear as vertical lines in panel (B). Variations in the number of counted individuals may be due to variation in sampling effort or to real change in population size. Asterisks in panel (A) show differences in sampling effort: \* corresponds to years that the counts were performed only in Paraná, and \*\* only in São Paulo. Sources for the numbers shown are [28,29,43–61] (A), [36–42,67] (B), and [21,27,42,62–64] (C).

## 4. Discussion

### 4.1. Geographic Range

The four *Amazona* species we studied showed marked differences in geographic range and, most likely, also in population size. The estimated areas of the geographic ranges varied over two orders of magnitude, from the approximately fifteen thousand square kilometers in *A. brasiliensis* to more than four hundred thousand square kilometers in *A. vinacea*. The mean estimated range was larger than the IUCN Extant area for all species, with 95% credible intervals including the IUCN Extant area for only one of them, *A. brasiliensis*. Both our estimated range area and the IUCN Extant areas approximate areas of occupancy as defined by Gaston and Fuller [68]. The marked disparity is likely a reflection of conservative caution in the definition of IUCN Extant areas and of extraordinary sampling coverage afforded by the use of citizen-science data in our estimates.

Geographic-range differences across species partially reflect environmental factors that limit their distribution. The range of *A. brasiliensis* appears to be limited by the highlands of the Serra do Mar [28], which also have high occupancy by *A. vinacea*. Indeed, *A. vinacea* is the only species to show evidence of a positive association between altitude and occupancy probability. Occupancy by *A. vinacea* is also positively associated with Atlantic and Araucaria Forest covers, even though the parrot's range extends beyond that of *Araucaria angustifolia* [17]. None of these associations—with altitude or with any type of forest cover—were evident from the analyses of the other three species—*A. brasiliensis*, *A. pretrei*, or *A. rhodocorytha*. Such lack of statistical association does not mean that they are biologically indifferent to forest cover. They are all cavity-nesters, and will not reproduce without access to tree holes, which are predominantly found in old-growth forests [28,29,66,69–71]. Instead, the focal areas of all three include extensive regions of forest (or of high or low altitude) that happen to not be occupied. This weakens the statistical association with occupancy covariates, not because they do not facilitate occupancy, but because unknown factors not included in our models may be further restricting the parrot distributions.

### 4.2. Population Size

Of the four species in this study, we only have a statistical estimate of global population size for *A. vinacea*. At around 8500 individuals [21], this estimate is nearly three times the number reported by the IUCN [72]. The local estimate of ~6000 *A. rhodocorytha* individuals for one 461 km<sup>2</sup> site in Espírito Santo, reported by Marsden et al. in 1998 [62], appears too high. This number, which implies a homogeneous density of 13 individuals per km<sup>2</sup> throughout the study site, is more than twice the number counted for the whole state of Espírito Santo by a different team ten years later [63]. There was either a dramatic population reduction in the state or these *A. rhodocorytha* numbers need reconsideration. There are no published estimates or counts of *A. rhodocorytha* for five of the states covered by the range map in Figure 1C. The species' global population size of 10,000 individuals reported by the IUCN [73] and the Brazilian Red List [74] may be reasonable, but neither source provides an explanation of how that number was obtained.

Any considerations about population sizes of *A. pretrei* and *A. brasiliensis* must be based solely on raw counts, as there are no published statistical estimates of population size for these species. Counts are difficult to compare because they do not quantify uncertainty about their values. They are also likely to underestimate real population size because they do not account for detection errors. In the absence of statistical estimates, however, counts offer a reasonable lower bound for population size. *A. pretrei* is the species with the largest counts, exceeding 20,000 individuals in 2006, 2008, and 2011, a number that is also greater than the 16,000 individuals cited by the species' IUCN Red List profile [75,76]. This species' well-known tendency to concentrate in only a few municipalities during the non-breeding season [39] reduces the probability that observers overlook large flocks and makes us relatively more confident of the accuracy of *A. pretrei*'s counts than of the others. Counts of *A. brasiliensis* reached more than 9000 individuals in 2018 [61,77], making it, possibly, the species with the smallest geographic range but the second highest population size in this study. Future research could be aimed at the question of whether *A. brasiliensis* presents an exception to the well-supported positive relationship between area of occupancy and local abundance [78].

#### 4.3. Seasonal Change in Geographic Range

Seasonal movements of aggregation and dispersion, influenced by the reproductive cycle and changes in food availability, are well-documented for *A. brasiliensis* [29], *A. pretrei* [39], and *A. vinacea* [21,27]. Dispersion occurs in the beginning of the breeding season (August–September), when breeding pairs abandon collective roosts to start spending the nights near the nest. By the end of the breeding season—December to March depending on the species—parrots aggregate again in collective roosts, which vary in size from dozens to thousands of individuals [21,27,29,39,79]. Aggregation and dispersal phases of *A. pretrei* occur in nearly non-overlapping parts of the species' range. By early Autumn, individuals concentrate in southeast Santa Catarina [39,80], and they spend the coolest months of the year in this region, feeding on abundant Paraná pine (*Araucaria angustifolia*) seeds [39] while other food resources are scarce [26]. Even though some individuals may overwinter in Rio Grande do Sul, the majority of the *A. pretrei* population spends this period in Santa Catarina, forming groups with thousands of individuals, in the municipalities of Paineira, Urupema, Lages, and São Joaquim [39]. Between July and September, *A. pretrei* individuals disperse back to breed in Rio Grande do Sul, reaching at this point their largest geographic range and smallest group sizes [39]. Providing evidence of range dynamics at a larger temporal scale, *A. pretrei*'s center of aggregation has not always been in southeast Santa Catarina. Reports from the 1970s show large wintering aggregations of more than 10,000 individuals in the municipality of Muitos Capões, northern Rio Grande do Sul [3,37,38,67]. By the early 1990s, however, this number had decreased to only a few tens of individuals [39], and larger groups began appearing in Southeast Santa Catarina [39,81]. This shift of more than 100 km to the north follows decades of intense exploration and widespread destruction of Paraná pine forests in RS, which peaked between the 1920s and 1950s [82]. Most likely, scarcity of their most important winter fallback food forced *A. pretrei* into the colder but still relatively abundant *Araucaria* forests of the new wintering grounds in Santa Catarina [81].

#### 4.4. Long-Term Changes in Geographic Range

Among the four species in our study, *A. vinacea* shows the strongest evidence of range contraction, with local extinctions in parts of Argentina and Paraguay since the 1970s [63,64]. With a historic range that covered southern Paraguay west of Misiones and all the way into central Paraguay to the northwest [63], the occurrence of *A. vinacea* outside Brazil is now restricted to three localities in Argentina [21,63,64] and two in Paraguay [21,63]. Both *A. vinacea* and *A. pretrei* are classified as critically endangered in Argentina [83], which may have had a historical population of the latter [84,85]. *A. pretrei* is rarely observed in Paraguay [23,86], where it is also classified as threatened [87]. Belton [38]



mentions the possible past occurrence of *A. pretrei* as far north as São Paulo state, in Brazil, but the validity of XIX century records that could backup such possibility is disputed [3,75]. Reviewing information about *A. brasiliensis*, Scherer-Neto [28] cites reports of XIX century sightings in northern Rio Grande do Sul and northeast Santa Catarina (see also [77]), but the validity of these reports, too, is questionable [3]. Even with reliable identification, though, past observation of any species far outside the present range is no firm evidence of range contraction. Individuals may wander away from their species' ranges, sometimes across oceans [88], with sightings in unexpected locations inevitably getting more attention than within a known range, even if they bear no consequence to population dynamics. Parrots introduce the additional complication of having been kept as pets for a long time, so that past sightings in odd places could also be of individuals escaped from captivity. To conclude, *A. rhodocorytha* has the least historical information of the four species, with perhaps one observation deserving special attention: one recent record in the state of Alagoas [89] dispels a previous suggestion of local extinction [3] and confirms the existence of a disjunct population in the extreme north of the distribution.

#### 4.5. Long-Term Change in Population Size

The time series of counts that we report for *A. vinacea* and *A. brasiliensis* show increasing numbers very likely due to an increase in sampling effort. The time series for *A. pretrei* shows relatively small variation for the last two and a half decades. After an apparent decline during the 1970s [37,38], *A. pretrei* counts increased to around 20,000 individuals in 1997. Such increase coincides with the period when *A. pretrei* was shifting its wintering aggregation to Southeast Santa Catarina, where counts have been carried out by the same research team since 1995. Counts of *A. brasiliensis* and *A. vinacea*, on the other hand, have been carried out by different research groups in different locations, with variable degrees of coordination. The highest counts of *A. brasiliensis*, for example, were obtained in 2015 (9176 individuals), and in 2018 (9112 individuals), when research teams visited all known roosts in São Paulo and Paraná. In 2019, however, when only Paraná roosts were visited, approximately 2000 fewer individuals were counted. Similar, effort-driven variation is evident in the *A. vinacea* time series, which had fewer than one thousand individuals counted annually from 2001 to 2013. *A. vinacea* counts have increased since 2014, with the implementation of annual coordinated counts performed at a number of sites, that increased gradually from 20, in 2014, to 67, in 2017. The only period for which we can draw statistical inference about temporal change in the *A. vinacea* population is the transition from 2016 to 2017 [21]. The estimates shown in Figure 3C account for detection error and for variation in effort between the two years. The credible intervals of the abundance estimates, broadly overlapping between the two years, provide no evidence of a substantial change. Future analysis of population trends will require more coordination and replication of counts. This will facilitate statistical analysis of count results and investigation of real trends in population size.

#### 4.6. Concluding Remarks

The future of the four parrot species analyzed in this study is threatened by two key environmental hazards: habitat loss and human exploitation [2]. *A. brasiliensis*, *A. pretrei*, *A. rhodocorytha*, and *A. vinacea* are all impacted by the destruction of the Atlantic Forest, especially because they nest in tree cavities that are much more common in old growth than in secondary forests [90]. Since the arrival of Europeans in South America, almost 90% of the original Atlantic Forest cover was lost [12]. The remaining forest is highly fragmented, with only 20% of its area contained in patches larger than 100 km<sup>2</sup>, and 83% of the patches being smaller than 50 hectares [12]. When not replaced by pasture or farmland, cleared forest gives way to exotic tree monocultures, such as *Pinus* and *Eucalyptus* [91]. In coastal areas intensely used by the tourism industry, cleared forests may also give way to urban expansion, which disproportionately affects *A. brasiliensis* [29]. The other primary threat to all four species, human exploitation, comes in the form of nest

poaching [8,69,74,92–96]. According to one study [8], nest poaching is the principal cause of nest failure for *A. vinacea*—with more than 80% of 25 monitored nests poached—and *A. brasiliensis*—with 50% of 78 monitored nests poached. Four initiatives have been promoting conservation, as well as research and monitoring of the four species throughout the last three decades: Projeto Charão (for *A. pretrei*, since 1991), Projeto para Conservação do Papagaio-de-cara-roxa (for *A. brasiliensis*, since 1997), Projeto Chauá (for *A. rhodocorytha*, since 2014), and the Programa Nacional para a Conservação do Papagaio-de-peito-roxo (for *A. vinacea*, since 2015). To improve knowledge about population dynamics and manage a response to environmental threats, it is essential that these and similar initiatives expand their reach. Continued tapping of citizen-science data will help to update knowledge about species' ranges. The estimation of abundance and validation of range maps, however, require observers on the ground. Much can be achieved just by sending observers to municipalities with higher uncertainty about species' occurrence, but one can go much further by practicing integration of citizen-science and professional research work on a routine basis. The combination of range mapping based on citizen-science and coordinated observation by research teams throughout the species' ranges offers a powerful tool for accurately monitoring the species' status and for assessing the consequences of management decisions.

**Supplementary Materials:** The following are available online at [www.mdpi.com/article/10.3390/d13090416/s1](http://www.mdpi.com/article/10.3390/d13090416/s1), Supplementary S1: The R and BUGS code for the models used in estimating the parrot's geographic range is available. Table S1: Compilation of the available counts for *Amazona brasiliensis* with the respective reference. Table S2: Compilation of the available counts for *Amazona pretrei* with the respective reference. Table S3: Compilation of the available counts and abundance estimates for *Amazona vinacea* with the respective reference.

**Author Contributions:** Conceptualization, V.Z. and G.F.; methodology, D.A.W.M.; software, D.A.W.M. and V.Z.; formal analysis, V.Z. and D.A.W.M.; investigation, V.Z. and G.F.; resources, V.Z., D.A.W.M., and G.F.; data curation, V.Z.; writing—original draft preparation, V.Z., D.A.W.M., and G.F.; supervision, G.F.; project administration, V.Z. and G.F.; funding acquisition, V.Z. and G.F. All authors have read and agreed to the published version of the manuscript.

**Funding:** V.Z. received fellowships from the Brazilian government's CAPES and PrInt/CAPES programs, as well as research funding from Funbio, Instituto Humanize, and The Rufford Foundation (19835-1 and 23709-2).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The R codes and datasets used for the analyses are openly available at GitHub at: <https://github.com/vivizulian/DataIntegrationModels> (accessed on 3 April 2021).

**Acknowledgments:** We are grateful to Reinaldo Guedes who volunteered his free time over the last twelve years to developing and maintaining WikiAves, the most successful citizen-science initiative in Brazil. This paper would not be possible without the help of thousands of bird observers who uploaded photos, audio recordings, and birding lists to eBird, WikiAves, and Xeno-canto. Glayson Bencke kindly shared his time and knowledge about parrot biology with us in several insightful conversations that contributed to shaping the best part of this paper. We also thank the three reviewers that helped improve the manuscript.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. BirdLife International. The IUCN Red List of Threatened Species. 2021. Available online: <https://www.iucnredlist.org/> (accessed on 2 February 2020).
2. Collar, N.J.; Juniper, A.T. Dimensions and Causes of the Parrot Conservation Crisis. In *New World Parrots in Crisis: Solutions from Conservation Biology*; Smithsonian Institution Press: Washington, DC, USA, 1992.
3. Juniper, T.; Parr, M. *Parrots: A Guide to the Parrots of the World*; Yale University Press: New Haven, CT, USA; London, UK, 1998.
4. Cockle, K.L.; Martin, K.; Drever, M.C. Supply of Tree-Holes Limits Nest Density of Cavity-Nesting Birds in Primary and Logged Subtropical Atlantic Forest. *Biol. Conserv.* **2010**, *143*, 2851–2857, doi:10.1016/j.biocon.2010.08.002.

5. Foley, J.A. Global Consequences of Land Use. *Science* **2005**, *309*, 570–574, doi:10.1126/science.1111772.
6. Berkunsky, I.; Quillfeldt, P.; Brightsmith, D.J.; Abbud, M.C.; Aguilar, J.M.R.E.; Alemán-Zelaya, U.; Aramburú, R.M.; Arce Arias, A.; Balas McNab, R.; Balsby, T.J.S.; et al. Current Threats Faced by Neotropical Parrot Populations. *Biol. Conserv.* **2017**, *214*, 278–287, doi:10.1016/j.biocon.2017.08.016.
7. Tella, J.L.; Hiraldo, F. Illegal and Legal Parrot Trade Shows a Long-Term, Cross-Cultural Preference for the Most Attractive Species Increasing Their Risk of Extinction. *PLoS ONE* **2014**, *9*, e107546, doi:10.1371/journal.pone.0107546.
8. Wright, T.F.; Toft, C.A.; Enkerlin-Hoeflich, E.; Gonzalez-Elizondo, J.; Albornoz, M.; Rodríguez-Ferraro, A.; Rojas-Suárez, F.; Sanz, V.; Trujillo, A.; Beissinger, S.R.; et al. Nest Poaching in Neotropical Parrots. *Conserv. Biol.* **2001**, *15*, 710–720, doi:10.1046/j.1523-1739.2001.015003710.x.
9. del Hoyo, J.; Elliott, A.; Sargatal, J.; Christie, D.A.; de Juana, E. *Handbook of the Birds of the World Alive*; Lynx Edicions: Barcelona, Spain, 2017.
10. Ribeiro, M.C.; Martensen, A.C.; Metzger, J.P.; Tabarelli, M.; Scarano, F.R.; Fortin, M.-J. The Brazilian Atlantic Forest: A Shrinking Biodiversity Hotspot. In *Biodiversity Hotspots*; Zochos, F.E., Habel, J.C., Eds.; Springer: Berlin/Heidelberg, Germany, 2011; ISBN 978-3-642-20991-8.
11. Tabarelli, M.; Aguiar, A.V.; Ribeiro, M.C.; Metzger, J.P.; Peres, C.A. Prospects for Biodiversity Conservation in the Atlantic Forest: Lessons from Aging Human-Modified Landscapes. *Biol. Conserv.* **2010**, *143*, 2328–2340, doi:10.1016/j.biocon.2010.02.005.
12. Ribeiro, M.C.; Metzger, J.P.; Martensen, A.C.; Ponzoni, F.J.; Hirota, M.M. The Brazilian Atlantic Forest: How Much Is Left, and How Is the Remaining Forest Distributed? Implications for Conservation. *Biol. Conserv.* **2009**, *142*, 1141–1153, doi:10.1016/j.biocon.2009.02.021.
13. Powers, R.P.; Jetz, W. Global Habitat Loss and Extinction Risk of Terrestrial Vertebrates under Future Land-Use-Change Scenarios. *Nat. Clim. Chang.* **2019**, *9*, 323–329, doi:10.1038/s41558-019-0406-z.
14. Vergara-Tabares, D.L.; Cordier, J.M.; Landi, M.A.; Olah, G.; Nori, J. Global Trends of Habitat Destruction and Consequences for Parrot Conservation. *Glob. Chang. Biol.* **2020**, *26*, 4251–4262, doi:10.1111/gcb.15135.
15. Vale, M.M.; Tourinho, L.; Lorini, M.L.; Rajão, H.; Figueiredo, M.S.L. Endemic Birds of the Atlantic Forest: Traits, Conservation Status, and Patterns of Biodiversity. *J. Field Ornithol.* **2018**, *89*, 193–206, doi:10.1111/jof.12256.
16. Mace, G.M.; Collar, N.J.; Gaston, K.J.; Hilton-Taylor, C.; Akçakaya, H.R.; Leader-Williams, N.; Milner-Gulland, E.J.; Stuart, S.N. Quantification of Extinction Risk: IUCN's System for Classifying Threatened Species. *Conserv. Biol.* **2008**, *22*, 1424–1442.
17. Zulian, V.; Miller, D.A.W.; Ferraz, G. Improving Estimation of Species Distribution from Citizen-Science Records Using Data-Integration Models. *bioRxiv* **2021**, doi:10.1101/2021.04.09.439158.
18. eBird. Available online: <https://ebird.org/home> (accessed on 2 February 2020).
19. WikiAves. WikiAves, a Enciclopédia Das Aves Do Brasil. Available online: <http://www.wikiaves.com.br> (accessed on 8 January 2020).
20. Xeno-Canto. Available online: <https://www.xeno-canto.org/> (accessed on 9 January 2019).
21. Zulian, V.; Müller, E.S.; Cockle, K.L.; Lesterhuis, A.; Tomasi Júnior, R.; Prestes, N.P.; Martinez, J.; Kéry, M.; Ferraz, G. Addressing Multiple Sources of Uncertainty in the Estimation of Global Parrot Abundance from Roost Counts: A Case Study with the Vinaceous-Breasted Parrot (*Amazona vinacea*). *Biol. Conserv.* **2020**, *248*, 108672, doi:10.1016/j.biocon.2020.108672.
22. MacKenzie, D.I.; Nichols, J.D.; Lachman, G.B.; Droege, S.; Andrew Royle, J.; Langtimm, C.A. Estimating Site Occupancy Rates When Detection Probabilities Are Less than One. *Ecology* **2002**, *83*, 2248–2255.
23. Collar, N.; Boesman, P.F.D. Red-spectacled Parrot (*Amazona pretrei*). In *Birds of the World*; Billerman, S.M., Keeney, B.K., Rodewald, P.G., Schulenberg, T.S., Eds.; Cornell Lab of Ornithology: Ithaca, NY, USA, 2020.
24. Collar, N.; Boesman, P.F.D.; Sharpe, C. Red-browed Parrot (*Amazona rhodocorytha*). In *Birds of the World*; Billerman, S.M., Keeney, B.K., Rodewald, P.G., Schulenberg, T.S., Eds.; Cornell Lab of Ornithology: Ithaca, NY, USA, 2020.
25. Collar, N.; Boesman, P.F.D.; Sharpe, C. Red-tailed Parrot (*Amazona brasiliensis*). In *Birds of the World*; Billerman, S.M., Keeney, B.K., Rodewald, P.G., Schulenberg, T.S., Eds.; Cornell Lab of Ornithology: Ithaca, NY, USA, 2020.
26. Prestes, N.P.; Martinez, J.; Peres, A.R. Dieta alimentar do papagaio-charão (*Amazona pretrei*). In *Biologia Da Conservação: Estudo de Caso com Papagaio-Charão e Outros Papagaios Brasileiros*; Martinez, J., Prestes, N.P., Eds.; UPF Editora: Passo Fundo, RS, Brazil, 2008.
27. Prestes, N.P.; Martinez, J.; Kilpp, J.C.; Batistela, T.; Turkievicz, A.; Rezende, É.; Gaboardi, V.T.R. Ecologia e Conservação de *Amazona vinacea* Em Áreas Simpátricas Com *Amazona pretrei*. *Ornithologia* **2014**, *6*, 109–120.
28. Scherer-Neto, P. Contribuição à Biologia do Papagaio-de-Cara-Roxa *Amazona Brasiliensis* (Linnaeus, 1758) (Psittacidae, Aves). Master's Thesis, Universidade Federal do Paraná, Curitiba, PR, Brazil, 1989.
29. Martuscelli, P. Ecology and Conservation of the Red-Tailed Amazon *Amazona brasiliensis* in South-Eastern Brazil. *Bird Conserv. Int.* **1995**, *5*, 405–420, doi:10.1017/S095927090000112X.
30. IBGE Mapa de Vegetação. 2012. Available online: <https://www.ibge.gov.br> (accessed on 30 June 2021).
31. Hijmans, R.J.; Guarino, L.; Cruz, M.; Rojas, E. Computer Tools for Spatial Analysis of Plant Genetic Resources Data: 1. DIVA-GIS. *Plant Genet. Resour. Newsl.* **2001**, *127*, 15–19.
32. Pacifici, K.; Reich, B.J.; Miller, D.A.W.; Gardner, B.; Stauffer, G.; Singh, S.; McKerrow, A.; Collazo, J.A. Integrating Multiple Data Sources in Species Distribution Modeling: A Framework for Data Fusion. *Ecology* **2017**, *98*, 840–850, doi:10.1002/ecy.1710.
33. Miller, D.A.W.; Pacifici, K.; Sanderlin, J.S.; Reich, B.J. The Recent Past and Promising Future for Data Integration Methods to Estimate Species' Distributions. *Methods Ecol. Evol.* **2019**, *10*, 22–37, doi:10.1111/2041-210X.13110.

34. Stauffer, G.E.; Miller, D.A.W.; Williams, L.M.; Brown, J. Ruffed Grouse Population Declines after Introduction of West Nile Virus. *Jour. Wild. Mgmt.* **2018**, *82*, 165–172, doi:10.1002/jwmg.21347.
35. Lunn, D.J.; Thomas, A.; Best, N.; Spiegelhalter, D. WinBUGS—a Bayesian Modelling Framework: Concepts, Structure, and Extensibility. *Stat. Comput.* **2000**, *10*, 325–337.
36. Forshaw, J.M.; Cooper, W.T. *Parrots of the World*, 2nd ed.; Lansdowne Press: Melbourne, Australia, 1978.
37. Varty, N.; Bencke, G.A.; Bernardini, L.M.; Cunha, A.S.; Dias, E.V.; Fontana, C.S.; Guadagnin, D.L.; Kindel, A.; Kindel, E.; Raymundo, M.M.; et al. *Conservação Do Papagaio-Charão Amazona pretrei No Sul Do Brasil: Um Plano de Ação Preliminar*; Divulgações do Museu de Ciências e Tecnologia UBEA/PUCRS: EDIPUCRS: Porto Alegre, RS, Brazil, 1994.
38. Belton, W. *Birds of Rio Grande Do Sul, Brazil. Part 1. Rheidae through Furnariidae*; Bulletin of the American Museum of Natural History: New York, NY, USA, 1984; Volume 178.
39. Martinez, J.; Prestes, N.P. Tamanho populacional, tamanho médio de bando e outros aspectos demográficos do papagaio-charão (*Amazona pretrei*). In *Biologia da Conservação: Estudo de Caso Com Papagaio-Charão e Outros Papagaios Brasileiros*; Martinez, J., Prestes, N.P., Eds.; UPF Editora: Passo Fundo, RS, Brazil, 2008.
40. Tella, J.L.; Dénes, F.V.; Zulian, V.; Prestes, N.P.; Martínez, J.; Blanco, G.; Hiraldo, F. Endangered Plant-Parrot Mutualisms: Seed Tolerance to Predation Makes Parrots Pervasive Dispersers of the Parana Pine. *Sci. Rep.* **2016**, *6*, 31709, doi:10.1038/srep31709.
41. Schunck, F.; Somenzari, M.; Lugarini, C.; Soares, E.S. *Plano de Ação Nacional Para a Conservação Dos Papagaios Da Mata Atlântica*; Instituto Chico Mendes de Conservação da Biodiversidade-ICMBio: Brasília, DF, Brazil, 2011.
42. ICMBio. Plano de Ação Nacional Para a Conservação Dos Papagaios—PAN Papagaios: Matriz de Monitoria. 2020. Available online: <https://www.icmbio.gov.br/portal/faunabrasileira/plano-de-acao-nacional-lista/837-plano-de-acao-nacional-para-conservacao-dos-papagaios-da-mata-atlantica> (accessed on 2 April 2020).
43. *SPVS Relatório Anual 2019*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, Brazil, 2019; p. 52.
44. Scherer-Neto, P.; Toledo, M.C. Avaliação Populacional Do Papagaio-de-Cara-Roxa (*Amazona brasiliensis*) (Psittacidae) No Estado Do Paraná, Brasil. *Ornitol. Neotrop.* **2007**, *18*, 379–393.
45. Galetti, M.; Schunck, F.; Ribeiro, M.; Paiva, A.A.; Toledo, R.; Fonseca, L. Distribuição e Tamanho Populacional Do Papagaio-de-Cara-Roxa *Amazona brasiliensis* No Estado de São Paulo. *Rev. Bras. Ornitol.* **2006**, *14*, 239–247.
46. *SPVS Relatório Anual 2003*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2003; p. 20.
47. *SPVS Relatório Anual 2004*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2004; p. 16.
48. *SPVS Relatório Anual 2005*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2005; p. 8.
49. *SPVS Relatório Anual 2006*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2006; p. 12.
50. *SPVS Relatório Anual 2007*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2007; p. 16.
51. *SPVS Relatório Anual 2008*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2008; p. 12.
52. *SPVS Relatório Anual 2009*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2009; p. 6.
53. *SPVS Relatório Anual 2010*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2010; p. 4.
54. *SPVS Relatório Anual 2011*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2011; p. 13.
55. *SPVS Relatório Anual 2012*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2012; p. 38.
56. *SPVS Relatório Anual 2013*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2013; p. 27.
57. *SPVS Relatório Anual 2014*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2014; p. 27.
58. *SPVS Relatório Anual 2015*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2015; p. 35.
59. *SPVS Relatório Anual 2016*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2016; p. 52.
60. *SPVS Relatório Anual 2017*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2017; p. 48.
61. *SPVS Relatório Anual 2018*; Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental: Curitiba, PR, Brazil, 2018; p. 44.
62. Abe, L.M. Caracterização do Hábitat do Papagaio-de-Peito-Roxo *Amazona vinacea* (Kuhl, 1820) No Município de Tunas do Paraná, Região Metropolitana de Curitiba, Paraná. Master's Thesis, Universidade Federal do Paraná, Curitiba, PR, Brazil, 2004.
63. Cockle, K.; Capuzzi, G.; Bodrati, A.; Clay, R.; del Castillo, H.; Velázquez, M.; Areta, J.I.; Fariña, N.; Fariña, R. Distribution, Abundance, and Conservation of Vinaceous Amazons (*Amazona vinacea*) in Argentina and Paraguay. *J. Field Ornithol.* **2007**, *78*, 21–39, doi:10.1111/j.1557-9263.2006.00082.x.
64. Segovia, J.M.; Cockle, K.L. Conservación del Loro Vinoso (*Amazona vinacea*) En Argentina. *El Hornero* **2012**, *27*, 27–37.
65. Marsden, S.J.; Whiffin, M.; Sadgrove, L.; Guimarães, P. Parrot Populations and Habitat Use in and around Two Lowland Atlantic Forest Reserves, Brazil. *Biol. Conserv.* **2000**, *96*, 209–217, doi:10.1016/S0006-3207(00)00071-9.
66. Klemann-Júnior, L.; Neto, P.S.; Monteiro, T.V.; Ramos, M.; de Almeida, R. Mapeamento da distribuição e conservação do chauá (*Amazona rhodocorytha*) no estado do Espírito Santo, Brasil. *Ornitol. Neotrop.* **2008**, *19*, 14.
67. Silva, F. Contribuição Ao Conhecimento Da Biologia Do Papagaio Charão, *Amazona pretrei* (TEMMINCK, 1830) (Psittacidae, Aves). *Iheringia Sér. Zool.* **1981**, *58*, 79–85.
68. Gaston, K.J.; Fuller, R.A. The Sizes of Species' Geographic Ranges. *J. Appl. Ecol.* **2009**, *46*, 1–9, doi:10.1111/j.1365-2664.2008.01596.x.
69. Prestes, N.P.; Martinez, J.; Meyrer, P.A.; Hansen, L.H.; Xavier, M. de N. Nest Characteristics of the Red-Spectacled Amazon *Amazona pretrei* Temminck, 1830 (Psittacidae). *Ararajuba* **1997**, *5*, 151–158.
70. Prestes, N.P.; Martinez, J.; Rezende, É. Biologia reprodutiva do papagaio-charão (*Amazona pretrei*). In *Biologia Da Conservação: Estudo de Caso com Papagaio-Charão e Outros Papagaios Brasileiros*; Martinez, J., Prestes, N.P., Eds.; Editora UPF: Passo Fundo, RS, Brazil, 2008; Volume 1.

71. Forshaw, J.M. *Parrots of the World*; Princeton field guides; Princeton University Press: Princeton, NJ, USA, 2010; ISBN 978-0-691-14285-2.
72. BirdLife International IUCN Red List of Threatened Species: *Amazona Vinacea*. 2017. Available online: <http://dx.doi.org/10.2305/IUCN.UK.2016-3.RLTS.T22686374A93109194.en> (accessed on 18 March 2019).
73. BirdLife International IUCN Red List of Threatened Species: *Amazona Rhodocorytha*. 2017. Available online: <https://dx.doi.org/10.2305/IUCN.UK.2017-3.RLTS.T22686288A118968809.en> (accessed on 18 March 2019).
74. ICMBio. Livro Vermelho da Fauna Brasileira Ameaçada de Extinção: Volume III—Aves. In *Livro Vermelho da Fauna Brasileira Ameaçada de Extinção*; Instituto Chico Mendes de Conservação da Biodiversidade. (Org.): Brasília, DF, Brazil, 2018; Volume 3, p. 712.
75. BirdLife International IUCN Red List of Threatened Species: *Amazona Pretrei*. 2016. Available online: <https://dx.doi.org/10.2305/IUCN.UK.2016-3.RLTS.T22686251A93104759.en> (accessed on 18 March 2019).
76. *Parrots: Status Survey and Conservation Action Plan, 2000-2004*; Snyder, N.F.R., McGowan, P., Gilardi, J., Grajal, A., Eds.; IUCN/SSC action plans for the conservation of biological diversity; IUCN: Gland, Switzerland, 2000; ISBN 978-2-8317-0504-0.
77. BirdLife International IUCN Red List of Threatened Species: *Amazona Brasiliensis*. 2017. Available online: <https://dx.doi.org/10.2305/IUCN.UK.2017-3.RLTS.T22686296A118478685.en> (accessed on 27 April 2021).
78. Holt, A.R.; Gaston, K.J.; He, F. Occupancy-Abundance Relationships and Spatial Distribution: A Review. *Basic Appl. Ecol.* **2002**, *3*, 1–13.
79. Sipinski, E.A.B.; Abbud, M.C.; Sezerban, R.M.; Serafini, P.P.; Boçon, R.; Manica, L.T.; de Camargo Guaraldo, A. Tendência Populacional Do Papagaio-de-Cara-Roxa (*Amazona brasiliensis*) No Litoral Do Estado Do Paraná. *Ornithologia* **2014**, *6*, 136–143.
80. Marini, M.Á.; Barbet-Massin, M.; Martinez, J.; Prestes, N.P.; Jiguet, F. Applying Ecological Niche Modelling to Plan Conservation Actions for the Red-Spectacled Amazon (*Amazona pretrei*). *Biol. Conserv.* **2010**, *143*, 102–112, doi:10.1016/j.biocon.2009.09.009.
81. Martinez, J.; Prestes, N.P. Um pouco da história do papagaio-charão (*Amazona pretrei*). In *Biologia da Conservação: Estudo de Caso Com Papagaio-Charão E Outros Papagaios Brasileiros*; Martinez, J., Prestes, N.P., Eds.; UPF Editora: Passo Fundo, RS, Brazil, 2008.
82. Martinez, J.; Prestes, N.P.; Rezende, É. As ameaças enfrentadas pelo papagaio-charão (*Amazona pretrei*). In *Biologia Da Conservação: Estudo de Caso com Papagaio-Charão e Outros Papagaios Brasileiros*; Martinez, J., Prestes, N.P., Eds.; Editora UPF: Passo Fundo, RS, Brazil, 2008.
83. Ministerio de Ambiente e Desarrollo Sustentable. Aves Argentinas. *Categorizacion de Las Aves de La Argentina Según Su Estado de Conservación*; Informe del Ministerio de Ambiente y Desarrollo Sustentable de la Nación y de Aves Argentinas: Buenos Aires, Argentina, 2015.
84. BirdLife International Handbook of the Birds of the World *Amazona Pretrei*. 2016. Available online: <https://dx.doi.org/10.2305/IUCN.UK.2016-3.RLTS.T22686251A93104759.en> (accessed on 18 March 2019).
85. Bodrati, A.; Cogle, K. New Records of Rare and Threatened Birds from the Atlantic Forest of Misiones, Argentina. *Cotinga* **2006**, *26*, 20–24.
86. Brooks, M.; Clay, R.P.; Lowen, C.; Butchart, H.M.; Barnes, R.; Esquivel, E.Z.; Etcheverry, N.I.; Vincent, J.P. New Information on Nine Birds from Paraguay. *Ornitol. Neotrop.* **1995**, *6*, 129–134.
87. Ministerio del Ambiente y Desarrollo Sostenible *Resolución n 254/19 Por La Cual Se Actualiza El Listado de Las Especies Protegidas de La Vida Silvestre de La Clase Aves*; Gobierno Nacional, Paraguay, 2019.
88. Alerstam, T. Ecological Causes and Consequences of Bird Orientation. *Experientia* **1990**, *46*, 405–415.
89. Roda, S.A. *Distribuição de aves Endêmicas e Ameaçadas em Usinas de Açúcar e Unidades de Conservação do Centro Pernambuco*; Centro de Pesquisas Ambientais do Nordeste: Recife, PE, Brazil, 2005; p. 42.
90. Katayama, M.V.; Zima, P.V.Q.; Perrella, D.F.; Francisco, M.R. Successional Stage Effect on the Availability of Tree Cavities for Cavity-Nesting Birds in an Atlantic Forest Park from the State of São Paulo, Brazil. *Biota Neotrop.* **2017**, *17*, doi:10.1590/1676-0611-bn-2017-0391.
91. Baptista, S.R.; Rudel, T.K. A Re-Emerging Atlantic Forest? Urbanization, Industrialization and the Forest Transition in Santa Catarina, Southern Brazil. *Environ. Conserv.* **2006**, *33*, 195, doi:10.1017/S0376892906003134.
92. Bonfanti, T.; Meurer, C.; Martinez, J.; Prestes, N.P. A captura de papagaios: Espécies encontradas em cativeiro no norte e nordeste do Rio Grande do Sul. In *Biologia Da Conservação: Estudo de Caso com Papagaio-Charão e Outros Papagaios Brasileiros*; Martinez, J., Prestes, N.P., Eds.; Editora UPF: Passo Fundo, RS, Brazil, 2008.
93. Martuscelli, P. A Parrot with a Tiny Distribution and a Big Problem: Will Illegal Trade Wipe out the Red-Tailed Amazon? *PsittaScene* **1994**, *6*, 3–7.
94. de Cavalheiro, M.L. Qualidade do Ambiente e Características Fisiológicas do Papagaio-de-Cara-Roxa (*Amazona brasiliensis*) Ilha Comprida-São Paulo. Master's Thesis, Universidade Federal do Paraná UFPR, Curitiba, PR, Brazil, 1999.
95. Carrillo, A.C.; Batista, D.B. A conservação do papagaio-da-cara-roxa (*Amazona brasiliensis*) no estado do Paraná: Uma experiência de Educação Ambiental no ensino formal. *Rev. Árvore* **2007**, *31*, 113–122, doi:10.1590/S0100-67622007000100013.
96. Cordeiro, P.H.C. A fragmentação da Mata Atlântica no sul da Bahia e suas implicações na conservação dos psitacídeos. In *Ecologia e conservação de psitacídeos no Brasil*; Melopsittacus Publicações Científicas: Belo Horizonte, MG, Brazil, 2002; p. 236.

## Supporting Information: Code

**Appendix S1:** Example of R and BUGS code for the models used in estimating the parrot's geographic range. The code includes the CAR component of the model, accounting for effort and site covariates.

```
## Extract the spatial adjacencies:

muni = readOGR("DISTRIBUTION.shp") #read the municipality shapefile

muni.centroids <- getSpPPolygonsLabptSlots(muni) #extract the centroids

make_grid <- function(x, cell_diameter, cell_area, clip = FALSE) {
  if (missing(cell_diameter)) {
    if (missing(cell_area)) {
      stop("Must provide cell_diameter or cell_area")
    } else {
      cell_diameter <- sqrt(2 * cell_area / sqrt(3))
    }
  }
  ext <- as(extent(x) + cell_diameter, "SpatialPolygons")
  projection(ext) <- projection(x)
  # generate array of hexagon centers
  g <- spsample(ext, type = "hexagonal", cellsize = cell_diameter,
               offset = c(0.5, 0.5))
  # convert center points to hexagons
  g <- HexPoints2SpatialPolygons(g, dx = cell_diameter)
  # clip to boundary of study area
  if (clip) {
    g <- gIntersection(g, x, byid = TRUE)
  } else {
    g <- g[x, ]
  }
  # clean up feature IDs
  row.names(g) <- as.character(1:length(g))
  return(g)
}

hex <- make_grid(muni, cell_diameter = .5)
hex.centroids <- getSpPPolygonsLabptSlots(hex)

cell.id <- c()
for (a in 1:nrow(muni.centroids)) {
  cell.id[a] <- which.min(sqrt((hex.centroids[,1]-
muni.centroids[a,1])^2+(hex.centroids[,2]-muni.centroids[a,2])^2))
}

## Convert the polygonal representation into a neighborhood list
hex.nb = poly2nb(hex)
num <- sapply(hex.nb,length)
sumNeigh <- sum(num)
adj = unlist(hex.nb)
```

```

#Data object specification in R
data <- list(muni1 = dat$IDENT, muni2 = dat2$IDENT, muni3 = dat3$IDENT,
            muni4 = dat4$IDENT, Y1 = dat$A_VINACEA, Y2 = dat2$A_VINACEA, Y3 =
            dat3$AVINACEA, Y4 = dat4$A_VINACEA, nMuni = length(muni), nObs1 =
            nrow(dat), nObs2 = nrow(dat2), nObs3 = nrow(dat3), nObs4 =
            nrow(dat4), TObs = dat$EFFORT_MIN/60, SSee = dat2$NSPECIES, TObs2
            = dat2$DURATION.M/60, RLen = dat2$EFFORT.DIS, NPho = dat3$NPIC,
            NAud = dat3$NSONG, NAud2 = dat4$NSONGS, VegCover = VegCover,
            ArauCover = ArauCover, Alt = Altitude, nCell =
            nrow(hex.centroids), cell.id = cell.id, nMuni = length(muni), adj
            = adj, num = num, sumNeigh = sumNeigh)

# Model specification in BUGS language
cat(file = "model.txt", "
model {
  #CAR prior - spatial random effect
  for(j in 1:sumNeigh){weights[j] <- 1}
  spacesigma ~ dunif(0,5)
  spacetau <- 1/(spacesigma*spacesigma)
  delta[1:nCell] ~ car.normal(adj[],weights[],num[],spacetau)

### data model

  for (i in 1:nMuni){ #loop over sites
    mu[i] <- alpha[cell.id[i]] + beta[1] + beta[2]*VegCover[i] +
    beta[3]*ArauCover[i] + beta[4]*Alt[i]
    mu.lim[i] <- min(10, max(-10, mu[i]))
    logit(psi[i]) <- mu.lim[i]
    z[i] ~ dbern(psi[i])
  }

  for (n in 1:nObs1){ #loop over observations - Count Data
    e1[n] <- BETA[1]*TObs[n]
    P1[n] <- 1-pow((1-0.5), e1[n])
    zP1[n] <- P1[n]*z[muni1[n]]
    Y1[n] ~ dbern(zP1[n])
  }

  for (j in 1:nObs2){ #loop over observations - eBird Data
    e2[j] <- BETA[2]*SSee[j] + BETA[3]*TObs2[j] + BETA[4]*RLen[j]
    P2[j] <- 1-pow((1-0.5), e2[j])
    zP2[j] <- P2[j]*z[muni2[j]]
    Y2[j] ~ dbern(zP2[j])
  }

  for (k in 1:nObs3){ #loop over observations - Wikiaves data
    e3[k] <- BETA[5]*NPho[k] + BETA[6]*NAud[k]
    P3[k] <- 1-pow((1-0.5), e3[k])
    zP3[k] <- P3[k]*z[muni3[k]]
    Y3[k] ~ dbern(zP3[k])
  }

  for (h in 1:nObs4){ #loop over observations - Xeno-Canto data

```

```

    e4[h] <- BETA[7]*NAud2[h]
    P4[h] <- 1-pow((1-0.5), e4[h])
    zP4[h] <- P4[h]*z[muni4[h]]
    Y4[h] ~ dbern(zP4[h])
  }

beta[1] ~ dunif(-10,10)
beta[2] ~ dunif(-10,10)
beta[3] ~ dunif(-10,10)
beta[4] ~ dunif(-10,10)

for (b in 1:7){
  BETA[b] ~ dnorm(0,0.0001)I(0,10000)
}

#compute the mean detection probability of each dataset:
muP1 <- mean(P1[])
muP2 <- mean(P2[])
muP3 <- mean(P3[])
muP4 <- mean(P4[])

}

#Back to R language:

#Specification of Initial Values
inits = function() {list(z = rep(1, data$nMuni))}
params <- c("beta", "psi", "z", "alpha", "muP1", "muP2", "muP3", "muP4",
           "muP5", "muP6", "muP7", "muP8", "Y2", "Y4", "Y6", "Y8",
           "spacesigma", "delta")

#MCMC settings
nc <- 3;  nb <- 150000;  ni <- 200000;  nt <- 100

out <- bugs(data = data, inits = inits, parameters.to.save = params,
           model.file = "model.txt", n.chains = nc, n.iter = ni,
           n.burnin = nb, n.thin = nthin, debug = TRUE)

```



## Supporting Information: Tables

**Table S1:** Compilation of the available counts for *Amazona brasiliensis* with the respective reference.

| Year | Counted number of individuals | Source of information            |
|------|-------------------------------|----------------------------------|
| 1989 | 1,581                         | Scherer-Neto, 1989               |
| 1993 | 1,550                         | Martuscelli, 1995                |
| 1994 | 1,988                         | Scherer-Neto and Toledo, 2007    |
| 1995 | 3,672                         | Scherer-Neto and Toledo, 2007    |
| 1996 | 2,294                         | Scherer-Neto and Toledo, 2007    |
| 1997 | 1,548                         | Scherer-Neto and Toledo, 2007    |
| 1998 | 1,965                         | Scherer-Neto and Toledo, 2007    |
| 1999 | 2,512                         | Scherer-Neto and Toledo, 2007    |
| 2000 | 3,452                         | Scherer-Neto and Toledo, 2007    |
| 2003 | 3,657                         | Galetti et al., 2006; SPVS, 2003 |
| 2004 | 6,589                         | Galetti et al., 2006; SPVS, 2004 |
| 2005 | 4,870                         | SPVS, 2005                       |
| 2006 | 3,000                         | SPVS, 2006                       |
| 2007 | 4,821                         | SPVS, 2007                       |
| 2008 | 4,100                         | SPVS, 2008                       |
| 2009 | 5,099                         | SPVS, 2009                       |
| 2010 | 5,000                         | SPVS, 2010                       |
| 2011 | 6,412                         | SPVS, 2011                       |
| 2012 | 4,141                         | SPVS, 2012                       |
| 2013 | 6,086                         | SPVS, 2013                       |
| 2014 | 7,451                         | SPVS, 2014                       |
| 2015 | 9,176                         | SPVS, 2015                       |
| 2016 | 8,380                         | SPVS, 2016                       |
| 2017 | 7,339                         | SPVS, 2017                       |
| 2018 | 9,112                         | SPVS, 2018                       |
| 2019 | 7,493                         | SPVS, 2019                       |

**Table S2:** Compilation of the available counts for *Amazona pretrei* with the respective reference.

| Year | Counted number of individuals | Source of information  |
|------|-------------------------------|--|
| 1971 | 10,000-30,000                 | Forshaw and Cooper, 1978; cited by Varty et al., 1994                              |
| 1972 | 10,000                        | W. Belton in Silva 1989; cited by Varty et al., 1994                               |
| 1975 | 5,000                         | Silva, 1981  |
| 1980 | 1,000                         | Silva, 1981  |
| 1981 | 10,000                        | R. Reis verb to N. Varty; cited by Varty et al., 1994                              |
| 1983 | 10,000                        | Belton, 1984   |
| 1986 | 8,000                         | COA pers. commun. to N. Varty; cited by Varty et al., 1994                         |
| 1988 | 10,000                        | COA pers. commun. to N. Varty; cited by Varty et al., 1994                         |
| 1989 | 9,500-14,000                  | COA pers. commun. to N. Varty/Scherer Neto 1991; cited by Varty et al., 1994       |
| 1990 | 30-70                         | J. Mahler pers. commun. to N. Varty/Scherer Neto 1991; cited by Varty et al., 1994 |
| 1991 | 15-200                        | COA pers. commun. to N. Varty/Scherer Neto 1991; cited by Varty et al., 1994       |
| 1992 | 7,000-7,500                   | Varty et al., 1994   |
| 1993 | 7,500-8,000                   | Varty et al., 1994   |
| 1994 | 8,000-8,500                   | Varty et al., 1994   |
| 1995 | 8,593                         | Martinez and Prestes, 2008   |
| 1996 | 11,590                        | Martinez and Prestes, 2008   |
| 1997 | 19,141                        | Martinez and Prestes, 2008   |
| 1998 | 19,913                        | Martinez and Prestes, 2008   |
| 1999 | 19,517                        | Martinez and Prestes, 2008   |
| 2000 | 16,232                        | Martinez and Prestes, 2008   |
| 2001 | 16,897                        | Martinez and Prestes, 2008   |
| 2002 | 18,418                        | Martinez and Prestes, 2008   |
| 2003 | 17,162                        | Martinez and Prestes, 2008   |
| 2004 | 16,772                        | Martinez and Prestes, 2008   |
| 2005 | 20,437                        | Martinez and Prestes, 2008   |
| 2006 | 21,598                        | Martinez and Prestes, 2008   |
| 2007 | 18,800                        | Martinez and Prestes, 2008   |
| 2008 | 21,311                        | Schunck et al., 2011   |
| 2009 | 15,658                        | Schunck et al., 2011   |
| 2010 | 16,657                        | Schunck et al., 2011   |

|      |        |  |
|------|--------|--|
| 2011 | 21,653 | Schunck et al., 2011                       |
| 2014 | 15,685 | Tella et al., 2016 citing unpublished data |
| 2017 | 20,128 | ICMBio, 2020                               |
| 2018 | 18,425 | ICMBio, 2020                               |
| 2019 | 19,872 | ICMBio, 2020                               |

**Table S3:** Compilation of the available counts and abundance estimates for *Amazona vinacea* with the respective reference.

| Year | Counted number of individuals | Estimated number of individuals | Source of information                          |
|------|-------------------------------|---------------------------------|--|
| 2001 | 464                           | —                               | Abe, 2004; Cockle et al., 2007                 |
| 2002 | 899                           | —                               | Abe, 2004                                      |
| 2003 | 906                           | —                               | Abe, 2004                                      |
| 2004 | 514                           | —                               | Abe, 2004                                      |
| 2005 | 423                           | —                               | Cockle et al., 2007; Segovia and Cockle, 2012  |
| 2007 | 203                           | —                               | Segovia and Cockle, 2012                       |
| 2008 | 214                           | —                               | Segovia and Cockle, 2012                       |
| 2009 | 214                           | —                               | Segovia and Cockle, 2012                       |
| 2010 | 125                           | —                               | Segovia and Cockle, 2012                       |
| 2011 | 911                           | —                               | Prestes et al., 2014; Segovia and Cockle, 2012 |
| 2012 | 747                           | —                               | Prestes et al., 2014                           |
| 2013 | 728                           | —                               | Prestes et al., 2014                           |
| 2014 | 1,752                         | —                               | N. Prestes, pers. commun.                      |
| 2015 | 3,160                         | —                               | N. Prestes, pers. commun.                      |
| 2016 | 3,888                         | 7,789 (c.i. 6,586- 9,184)       | Zulian et al., 2020                            |
| 2017 | 4,084                         | 8,483 (c.i. 7,181- 9977)        | Zulian et al., 2020                            |
| 2018 | 4,758                         | —                               | ICMBio, 2020                                   |

## References:

- Abe, L.M., 2004. Caracterização do hábitat do papagaio-de-peito-roxo *Amazona vinacea* (Kuhl, 1820) no município de Tunas do Paraná, região metropolitana de Curitiba, Paraná (Dissertação de mestrado: Ciência do solo). Universidade Federal do Paraná, Curitiba, PR.
- Belton, W., 1984. Birds of Rio Grande do Sul, Brazil. Part 1. Rheidae through Furnariidae. Bulletin of the American Museum of Natural History, New York.
- Cockle, K., Capuzzi, G., Bodrati, A., Clay, R., del Castillo, H., Velázquez, M., Areta, J.I., Fariña, N., Fariña, R., 2007. Distribution, abundance, and conservation of Vinaceous Amazons (*Amazona vinacea*) in Argentina and Paraguay. Journal of Field Ornithology 78, 21–39. <https://doi.org/10.1111/j.1557-9263.2006.00082.x>
- Forshaw, J.M., Cooper, W.T., 1978. Parrots of the world, Second Edition. ed. Lansdowne Press, Melbourne, Australia.
- Galetti, M., Schunck, F., Ribeiro, M., Paiva, A.A., Toledo, R., Fonseca, L., 2006. Distribuição e tamanho populacional do papagaio-de-cara-roxa *Amazona brasiliensis* no estado de São Paulo. Revista Brasileira de Ornitologia 239–247.
- ICMBio, 2020. Plano de Ação Nacional para a Conservação dos Papagaios - PAN Papagaios: Matriz de Monitoria.
- Martinez, J., Prestes, N.P., 2008. Tamanho populacional, tamanho médio de bando e outros aspectos demográficos do papagaio-charão (*Amazona pretrei*), in: Martinez, J., Prestes, N.P. (Eds.), Biologia Da Conservação: Estudo de Caso Com Papagaio-Charão e Outros Papagaios Brasileiros. UPF Editora, Passo Fundo, RS.
- Martuscelli, P., 1995. Ecology and conservation of the Red-tailed Amazon *Amazona brasiliensis* in south-eastern Brazil. Bird Conservation International 5, 405–420. <https://doi.org/10.1017/S095927090000112X>
- Prestes, N.P., Martinez, J., Kilpp, J.C., Batistela, T., Turkievicz, A., Rezende, É., Gaboardi, V.T.R., 2014. Ecologia e conservação de *Amazona vinacea* em áreas simpátricas com *Amazona pretrei*. Ornithologia 6, 109–120.
- Scherer-Neto, P., 1989. Contribuição à biologia do papagaio-de-cara-roxa *Amazona brasiliensis* (Linnaeus, 1758) (Psittacidae, Aves) (Dissertação de Mestrado: Zoologia). Universidade Federal do Paraná, Curitiba, PR.
- Scherer-Neto, P., Toledo, M.C., 2007. Avaliação populacional do papagaio-de-cara-roxa (*Amazona brasiliensis*) (Psittacidae) no Estado do Paraná, Brasil. Ornithologia Neotropical 18, 379–393.
- Schunck, F., Somenzari, M., Lugarini, C., Soares, E.S., 2011. Plano de Ação Nacional para a Conservação dos Papagaios da Mata Atlântica. Instituto Chico Mendes de Conservação da Biodiversidade - ICMBio, Brasília.
- Segovia, J.M., Cockle, K.L., 2012. Conservación del Loro vinoso (*Amazona vinacea*) en Argentina. El hornero 27, 027–037.
- Silva, F., 1981. Contribuição ao conhecimento da biologia do papagaio charão, *Amazona pretrei* (TEMMINCK, 1830) (Psittacidae, Aves). Iheringia. Sér. Zool. 58, 79–85.
- SPVS, 2019. Relatório Anual 2019. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.

- SPVS, 2018. Relatório Anual 2018. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2017. Relatório Anual 2017. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2016. Relatório Anual 2016. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2015. Relatório Anual 2015. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2014. Relatório Anual 2014. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2013. Relatório Anual 2013. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2012. Relatório Anual 2012. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2011. Relatório Anual 2011. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2010. Relatório Anual 2010. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2009. Relatório Anual 2009. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2008. Relatório Anual 2008. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2007. Relatório Anual 2007. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2006. Relatório Anual 2006. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2005. Relatório Anual 2005. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2004. Relatório Anual 2004. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- SPVS, 2003. Relatório Anual 2003. Sociedade de Pesquisa em Vida Selvagem e Educação Ambiental, Curitiba, PR.
- Tella, J.L., Dénes, F.V., Zulian, V., Prestes, N.P., Martínez, J., Blanco, G., Hiraldo, F., 2016. Endangered plant-parrot mutualisms: seed tolerance to predation makes parrots pervasive dispersers of the Parana pine. *Scientific Reports* 6, 31709. <https://doi.org/10.1038/srep31709>
- Varty, N., Bencke, G.A., Bernardini, L.M., Cunha, A.S., Dias, E.V., Fontana, C.S., Guadagnin, D.L., Kindel, A., Kindel, E., Raymundo, M.M., Richter, M., Rosa, A.O., Tostes, C.A.S., 1994. Conservação do papagaio-charão *Amazona pretrei* no sul do Brasil: um plano de ação preliminar. Divulgações do Museu de Ciências e Tecnologia UBEA/PUCRS: EDIPUCRS, Porto Alegre, RS.
- Zulian, V., Müller, E.S., Cockle, K.L., Lesterhuis, A., Tomasi Júnior, R., Prestes, N.P., Martinez, J., Kéry, M., Ferraz, G., 2020. Addressing multiple sources of uncertainty in the

estimation of global parrot abundance from roost counts: A case study with the  
Vinaceous-breasted Parrot (*Amazona vinacea*). *Biological Conservation* 248, 108672.  
<https://doi.org/10.1016/j.biocon.2020.108672>

## 8. RESULTADOS GERAIS

A área de distribuição estimada para cada uma das quatro espécies deste estudo—*A. vinacea*, *A. pretrei*, *A. brasiliensis* e *A. rhodocorytha*—foi maior do que a calculada a partir dos mapas de distribuição disponíveis na IUCN. O tamanho das áreas estimadas variou de 15.000 km<sup>2</sup> para *A. brasiliensis* até 434.000 km<sup>2</sup> para *A. vinacea*. As covariáveis de sítio cobertura de Mata Atlântica, cobertura de Floresta com Araucária e altitude ajudaram a explicar a ocorrência de *A. vinacea*, apresentando um efeito positivo na probabilidade de ocupação desta espécie. Para as demais espécies, não houve evidência de efeito de covariáveis de sítio na probabilidade de ocupação, já que os intervalos de credibilidade de 95% das estimativas incluíram zero.

A partir das comparações entre modelos de ocupação de sítio, observamos que o modelo integrando os dados de pesquisa com as três bases de dados de ciência cidadã produziu melhores predições acerca da distribuição de *A. vinacea*. Além disso, a inclusão da autocorrelação espacial, das covariáveis de sítio e das covariáveis de esforço amostral também aumentou o poder preditivo do modelo. A integração de diferentes conjuntos de dados em um modelo de *joint-likelihood* produziu uma representação mais acurada e precisa da distribuição da espécie do que qualquer conjunto de dados usados individualmente.

Em relação ao tamanho populacional, *A. vinacea*, apesar de ter o menor tempo de monitoramento (desde 2001), é a única espécie que possui uma estimativa estatística de abundância, a qual leva em consideração as variações temporais no esforço amostral e os erros de detecção. A abundância global da espécie é de  $7.789 \pm 655$  para 2016 e  $8.483 \pm 693$  indivíduos para 2017. Não observamos evidência de crescimento populacional de *A. vinacea* entre os dois anos analisados. *Amazona pretrei*, por outro lado, possui a série temporal mais longa de monitoramento (desde os anos 70) e o maior número de indivíduos contados e, desde

2007, as contagens se concentram em torno de 20.000 indivíduos. A segunda série temporal mais longa é a de *A. brasiliensis*, que conta com monitoramento desde o final dos anos 80 e tem as contagens das últimas três décadas sempre abaixo de 10.000 indivíduos. Para *A. rhodocorytha*, que não possui um programa de monitoramento, o Plano de Ação Nacional para Conservação dos Papagaios da Mata Atlântica reporta um tamanho populacional de 10.000 indivíduos com base em opinião de peritos, mas nenhuma informação demográfica adicional está disponível.

## 9. CONSIDERAÇÕES FINAIS

Os resultados dessa tese são muito mais do que as estimativas de tamanho populacional e de área de distribuição de quatro papagaios ameaçados na Mata Atlântica. Algumas lições aprendidas podem ser aplicadas a qualquer organismo de estudo:

- 1) Conhecer minimamente a biologia da espécie foco é essencial para delinear a amostragem. O fato de os papagaios se reunirem em dormitórios coletivos durante o período não reprodutivo facilitou as contagens e auxiliou na obtenção de estimativas de abundância mais precisas.
- 2) O delineamento amostral deve levar em consideração as possíveis análises estatísticas que serão utilizadas para responder a pergunta de estudo. Definimos previamente que utilizaríamos modelos *N-mixture* para estimar a abundância e modelos de ocupação de sítio para estimar a área de distribuição dos papagaios. A partir disso, desenhamos as amostragens e definimos quais dados precisávamos para cada uma das análises.
- 3) A análise de tendência populacional de espécies só é possível a partir de quantificação da incerteza. Monitoramentos longos, mas sem contagens replicadas, dificultam a diferenciação entre alterações reais no tamanho populacional e alterações devido a mudanças no esforço amostral.



- 4) O mapeamento de distribuição de espécies com base em dados de detecção/não-detecção que incluem informação sobre esforço amostral resultam em mapas informativos. A partir do uso de dados de detecção/não-detecção, é possível separar as ausências verdadeiras das falhas de detecção e obter mapas da incerteza associada às estimativas. Esses mapas informam os locais foco para amostragens futuras.
- 5) Plataformas de ciência cidadã e a integração de dados de diferentes fontes se mostraram uma ferramenta valiosa para estudos sobre área de distribuição das espécies podendo auxiliar na categorização de ameaças das espécies, bem como na análise de resultados das ações de conservação.
- 6) Resultados de predições com base em mapas da IUCN precisam ser interpretadas com cautela. Observamos que os mapas de distribuição apresentados pela IUCN para as quatro espécies de papagaios são muito diferentes dos estimados em nosso estudo. Se o mapa da IUCN fosse tomado como base, poderíamos chegar a conclusões precipitadas sobre alteração passada ou futura na área de distribuição das espécies.

A perda de habitat e roubo de filhotes são os fatores que mais afetam as populações de papagaios atualmente. Por isso, os estudos sobre tamanho populacional e distribuição são essenciais para tomada de decisões de manejo e conservação das espécies. Programas de monitoramento de psitacídeos que levem em consideração as fontes de incerteza por meio de protocolos de campo adequados e análises estatísticas, para melhor informar as avaliações do tamanho da população, área de distribuição, tendências e status de ameaça são essenciais para a conservação das espécies.