Francisco Voeroes Dénes

**Abundância de aves de rapina no Cerrado e Pantanal do
Mato Grosso do Sul e os efeitos da degradação de hábitat:
perspectivas com métodos baseados na detectabilidade**

**Raptor abundance in the Brazilian Cerrado and Pantanal:
insights from detection-based methods**

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Biociências da Universidade de
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Orientador: Dr. Luís Fábio Silveira

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Prof(a). Dr(a).

Prof(a). Dr(a).

Prof(a). Dr(a).

Prof(a). Dr(a).

Prof. Dr. Luís Fábio Silveira
(orientador)

À minha família.

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Introdução Geral

A perda de hábitat causada pelo crescimento populacional e desenvolvimento humano é ainda a principal causa do empobrecimento da biodiversidade (Savard et al. 2000). Em biomas neotropicais, a urbanização e a expansão das fronteiras agrícolas estão entre os principais fatores de degradação dos habitats naturais (Carrete et al. 2009). A preocupação crescente com os efeitos de mudanças antrópicas de grande escala cria a demanda por investigações e monitoramentos da qualidade ambiental e da biodiversidade para detectar variações na integridade biológica em grandes áreas geográficas (Carrete et al. 2009). No entanto, devido à complexidade da biodiversidade, a medição direta da qualidade de ecossistemas é uma tarefa muito difícil (Margules e Pressey 2000). Uma ferramenta útil para esse fim é o uso de espécies indicadoras, cuja presença, abundância ou densidade refletem a qualidade ambiental e a biodiversidade, e um objetivo comum de sua aplicação é a estimativa da similaridade ou diferença entre áreas (Margules e Pressey 2000). O uso de espécies indicadoras é uma tradição firmemente estabelecida em ecologia, toxicologia ambiental, controle de poluição e manejo agropecuário, florestal e ambiental (Sergio et al. 2008).

As aves de rapina diurnas, aqui definidas como incluindo representantes das ordens Cathartiformes (urubus e condores), Accipitriformes (gaviões, águias e abutres) e Falconiformes (falcões e caracará), são usualmente consideradas indicadores apropriados para o monitoramento de mudanças ambientais na escala de ecossistemas por serem predadores de topo (com exceção das espécies de menor porte, que tendem a ser insetívoras) ou carniceiros de vida longa, ocorrerem ao longo de gradientes de perturbações antrópicas de hábitat, desde vegetações primárias a áreas metropolitanas, e pelo fato de que algumas espécies são frequentemente associadas a habitat ou recursos específicos (Newton 1979, Sanchez-Zapata et al. 2003, Tella et al. 2008). Por exemplo, o gavião-belo *Busarellus*

1 *nigricollis* (Fig. 1) é especializado em caçar peixes de rios e lagoas, e o gavião-caramujeiro
2 *Rosthramus sociabilis* (Fig. 2) consome quase exclusivamente caramujos do gênero *Pomacea*
3 (Ferguson-Lees e Christie 2001). No entanto, detalhes da história-natural de muitas espécies
4 neotropicais ainda são pouco conhecidos devido às baixas densidades populacionais e à
5 relativa escassez de pesquisadores dedicados ao grupo (Olmos et al. 2006, Granzinolli 2009).
6 As poucas pesquisas com ecologia de aves de rapina sul-americanas têm sido voltadas
7 principalmente para as espécies florestais (Thiollay 1989, Jullien & Thiollay 1996, Manosa et
8 al. 2003, Roda & Pereira 2006), com a exceção de Albuquerque et al. (1986) e Zilio et al.
9 (2013), nos campos do Rio Grande do Sul. Apenas recentemente outros biomas passaram a
10 ser contemplados, como os Llanos Venezuelanos (Jensen et al. 2005) e o Cerrado em Goiás
11 (Baumgarten 1998, 2007) e São Paulo (Granzinolli 2009, Barros et al. 2010).

12 Na paisagem dominada por agropecuária de Itirapina, São Paulo, Granzinolli (2009)
13 verificou que pastagens extensivas e áreas de vegetação natural do Cerrado foram
14 selecionadas por, respectivamente, 4 e 7 das 15 aves de rapina da região, e que as
15 monoculturas em geral, e cana-de-açúcar em especial, foram rejeitadas por todas as espécies
16 do grupo. Carrete *et al.* (2009) relacionaram a riqueza, diversidade e abundância de aves de
17 rapina com a degradação de hábitat (transformação e fragmentação) em diversos biomas na
18 Argentina, e verificaram que tanto a riqueza quanto a diversidade de espécies foram maiores
19 em habitats naturais ou mistos, com um declínio pronunciado em paisagens mais
20 transformadas, e que a maioria das espécies teve sua abundância afetada negativamente pela
21 transformação de hábitat.

22 No entanto, o papel das aves de rapina como indicadores da qualidade ambiental
23 também tem sido alvo de controvérsia. Foi demonstrado que populações de aves de rapina
24 podem se beneficiar de algumas atividades humanas se novas fontes de alimentação ou
25 estruturas para caça ou nidificação tornarem-se disponíveis, tanto em ambientes tropicais da

1 América (Vannini 1989) como em zonas temperadas na Europa (Cardador et al. 2011). No
2 ambiente árido da Baja Califórnia, México, foi constatado que as populações da maioria das
3 espécies de rapinantes não declinaram em resultado de perda pequena a moderada de
4 vegetação natural cactáceo-arbustiva por conversão em agricultura irrigada. Ainda, a riqueza
5 de espécies não apresentou padrão de distribuição claramente relacionado com as
6 transformações de hábitat (Rodríguez-estrella et al. 1998). Já a conversão parcial ou
7 moderada de hábitat natural em ambientes florestais para pastagens ou agricultura,
8 aumentando a heterogeneidade da paisagem, pode favorecer a co-ocorrência de rapinantes
9 florestais e de habitats abertos resultando num aumento regional da diversidade, como
10 observado na floresta tropical de terras baixas em Honduras (Anderson 2001).

11 A partir dos estudos relatados acima pode-se concluir que a resposta do grupo das
12 aves de rapina à transformação de habitats, e consequentemente sua utilização como
13 indicadores de biodiversidade e qualidade ambiental, é altamente dependente do contexto, ou
14 seja, de quais espécies compõem a comunidade em determinada área, dos habitats naturais ali
15 presentes e dos tipos de perturbação aos quais estão sujeitos. A perda e degradação de hábitat
16 é um processo que vem se intensificando na maioria das formações naturais não-florestais do
17 Brasil, como o Cerrado e o Pantanal.

19 **Habitats naturais e sua degradação no Cerrado e Pantanal**

20 O Cerrado tem um clima sazonal com verões quentes e úmidos e invernos amenos e secos,
21 sendo que o período seco se estende por 3-5 meses consecutivos entre maio e setembro
22 (Cardoso e Bates 2002). A maior parte do Cerrado é recoberta por cerrado, que é uma
23 vegetação savânica semi-decídua a perene que se estabelece em solos profundos, bem
24 drenados e com poucos nutrientes. Essa vegetação varia em fisionomia e composição, com
25 cinco tipos estruturais geralmente reconhecidos (Cardoso e Bates 2002): (1) cerradão, uma

1 floresta densa, com dossel de 8-15 m de altura que frequentemente é fechado, (2) cerrado
2 *sensu stricto*, uma savana com extrato arbustivo fechado e extrato arbóreo mais baixo (5-8 m)
3 e ralo que no cerradão, (3) campo cerrado, uma savana aberta com poucas árvores baixas (3-6
4 m), (4) campo sujo, com arbustos dispersos que em geral atingem entre 2-3 metros de altura,
5 e (5) campo limpo, com extratos arbustivo e arbóreo extremamente ralos ou ausentes.
6 Adicionalmente, florestas de galeria com dossel entre 20-30 m e sub-bosque baixo e denso
7 ocorrem ao longo dos rios e riachos, e manchas de florestas secas semi-decíduas e decíduas
8 ocorrem em áreas de solo moderadamente mais produtivo.

9 O Pantanal é uma das maiores extensões alagadas contínuas do planeta (Mittermeier
10 et al. 1990). O clima consiste de verões quentes e chuvosos (novembro a março) e invernos
11 secos e amenos entre abril e outubro, com períodos mais frios ocasionais (Harris et al. 2005).
12 O pulso sazonal de enchente, que segue um ciclo anual mono-modal com amplitudes de 2-5
13 m e duração de 3 a 6 meses, é o principal condicionante dos padrões e processos ecológicos
14 no Pantanal (Harris et al. 2005). O pico da enchente leva cerca de quatro meses para
15 percorrer a bacia de norte a sul, de modo que quando atinge a região sul do Pantanal, a
16 estação seca (i.e., de baixa precipitação) já está em progresso. O sistema também é sujeito a
17 variações anuais na intensidade das enchentes (Junk et al. 2006). Sob influência da
18 Amazônia, Cerrado, Chaco e Floresta Atlântica, a vegetação do Pantanal é muito
19 heterogênea, com grande variabilidade de habitats, tipos de solo e regimes de inundação,
20 resultando em paisagens de mosaico muito variadas. As formações predominantes são
21 campos, cerradão, cerrado *sensu stricto*, brejos, floresta semi-decídua, floresta de galeria, e
22 vegetação aquática flutuante.

23 O domínio do Cerrado, que é considerado um *hotspot* de biodiversidade, já teve cerca
24 de 70% de sua extensão original convertida em pastagens e agricultura, e apenas 1,2-1,6% se
25 encontra protegido atualmente (Myers et al. 2000, Machado et al. 2004, Silva et al. 2006). A

1 agricultura na região consiste principalmente de culturas anuais como soja, milho e algodão,
2 assim como monoculturas de cana-de-açúcar e eucalipto. A perda de hábitat no Pantanal
3 também vem crescendo; cerca de 40% das florestas e savanas já foram transformadas com a
4 introdução de gramíneas exóticas para a criação de gado. Apesar de ser considerada uma
5 Reserva da Biosfera, apenas 2,5% da região se encontra formalmente protegida (Harris et al.
6 2005).

7 A resposta das comunidades e populações de aves às mudanças de hábitat no Cerrado
8 e Pantanal se tornou recentemente o foco de pesquisas, em decorrência da rapidez com que
9 amplas áreas dessas regiões foram convertidas em pastagens e plantações (Cardoso e Bates
10 2002, Harris et al. 2005). Por exemplo, além dos resultados obtidos por Granzinolli (2009),
11 descritos acima, pode-se citar o estudo por Tubelis e Cavalcanti (2000), que verificaram que
12 pastagens no Cerrado apresentam menor abundância e diferente composição da comunidade
13 de Passeriformes quando comparadas à habitats naturais.

15 **Inferência e estimativas de abundância em populações animais não-marcadas**

16 Estudos de dinâmica populacional e de impactos de mudanças ambientais, e projetos de
17 manejo e conservação são cada vez mais necessários no atual momento de intensa pressão
18 das atividades humanas sobre ambientes naturais e espécies selvagens. Estimativas de
19 abundância são importantes para que essas investigações e projetos sejam efetivos, pois
20 permitem que questões fundamentais sejam respondidas, como “quantos indivíduos
21 existem?”, “qual o efeito de uma mudança ambiental no tamanho da população?” ou “a
22 população está aumentando ou diminuindo?”. Um dos critérios mais importantes para a
23 definição de status de conservação utilizados pela União Internacional para a Conservação da
24 Natureza, por exemplo, é o tamanho populacional (IUCN, 2014).

1 Idealmente, um censo contabilizando todos os indivíduos é a maneira mais fiel de
2 quantificar uma população. No entanto, essa atividade é impraticável para a maioria das
3 espécies de animais selvagens – as raras situações que a permitem geralmente envolvem
4 populações pequenas em áreas restritas (Marques et al. 2013). Logo, pesquisadores
5 frequentemente se veem obrigados a realizar amostragens, onde contabilizam uma parte da
6 população e utilizam a abundância relativa (i.e., a própria contagem) ou algum índice de
7 abundância (e.g., indivíduos detectados por unidade de esforço) para fazer inferências sobre
8 fatores que influenciam populações ou para estimar o tamanho populacional e dinâmicas
9 associadas (Buckland et al. 2008). Contudo, processos como estocasticidade demográfica
10 (Martin et al. 2005), emigração temporária (Tyre et al. 2003, Chandler et al. 2011) e detecção
11 imperfeita (MacKenzie et al. 2002) podem introduzir variabilidade em dados de contagens de
12 indivíduos e, quando ignorados, podem mascarar padrões ecológicos importantes e induzir
13 estimativas enviesadas de abundância (Wenger e Freeman 2008).

14 O tema da detecção imperfeita tem sido cada vez mais discutido na literatura
15 ecológica na última década, em consequência do reconhecimento de sua importância em
16 estudos de ecologia de populações e de comunidades, (e.g., MacKenzie et al. 2002, Martin et
17 al. 2005, Royle e Dorazio 2008). O reconhecimento de que a detecção perfeita (i.e., todos os
18 indivíduos presentes são detectados) é rara em dados ecológicos levou ao desenvolvimento
19 de numerosos e diversos métodos analíticos para estimativa de abundância que lidam com
20 erros de detecção em contagens de populações não-marcadas (i.e., sem identificação
21 individual), incorporando formalmente o processo de detecção e diferenciando-o dos
22 processos ecológicos que influenciam a abundância (Buckland et al. 2001, Royle e Dorazio
23 2008, Sólymos et al. 2012).

1 **Justificativa**

2 Este trabalho tem dois objetivos principais. O fenômeno da detecção imperfeita, que ocorre
3 quase universalmente em amostragens de animais selvagens, pode introduzir importantes
4 erros e vieses em estimativas de tamanho populacional e riqueza (Iknayan et al. 2014). Novos
5 métodos analíticos que levam em conta a detectabilidade, como os modelos hierárquicos de
6 abundância, e ferramentas de computação como a plataforma R para análises estatísticas (R
7 Development Core Team 2014), vêm permitindo aos pesquisadores avançar em pesquisas
8 aplicadas à conservação, apesar dessas dificuldades. Contudo, a complexidade estatística das
9 técnicas e as diferenças nas suas premissas teóricas e pré-requisitos de desenho amostral
10 torna desafiadora a tarefa de escolher o método mais adequado para uma determinada
11 situação, particularmente para pesquisadores que não possuem familiaridade com as
12 metodologias estatísticas, os programas de computação e a literatura especializada. O
13 primeiro objetivo, portanto, é revisar os métodos mais comumente utilizados e/ou
14 recentemente desenvolvidos para modelagem e estimativa de abundância de populações não-
15 marcadas, com foco em como cada método incorpora o fenômeno da detecção imperfeita, e
16 discutindo suas premissas e pré-requisitos amostrais, com o objetivo de tornar os recentes
17 avanços estatísticos mais acessíveis para ecólogos que buscam estimar tamanho de
18 populações naturais.

19 Considerando que pressões antrópicas como as citadas acima vêm se tornando cada
20 vez maiores sobre o Cerrado e o Pantanal (Cardoso e Bates 2002, Harris et al. 2005),
21 justifica-se plenamente a preocupação pela conservação da biodiversidade desses ambientes,
22 da qual as aves constituem parcela significativa com alto valor biológico. Neste contexto,
23 embora a maioria das aves de rapina destes biomas não esteja globalmente ameaçada (IUCN
24 2014), o baixo grau de conhecimento sobre a ecologia dessas espécies, particularmente sobre
25 como suas populações respondem à degradação de habitats naturais e à transformação em

1 ambientes antrópicos, é alarmante. Estudos que avaliem adequadamente como essas possíveis
2 ameaças influenciam essas espécies são, portanto, necessários (Bierregaard 1998, Jensen et
3 al. 2005). Assim, este estudo pretende também descrever como transformações de habitat no
4 Cerrado e Pantanal do Mato Grosso do Sul (MS) impactaram as populações de 12 espécies de
5 aves de rapina (Tabela 1) em uma escala regional. Para isso, foi empregado um método de
6 modelagem de abundância que leva em conta a detectabilidade para investigar como a
7 abundância de cada espécie, estimada a partir de dados de contagens obtidos durante
8 amostragens de transecções com veículos em estradas (*road-surveys*) percorrendo ~1740 km
9 no Cerrado e Pantanal do MS, é influenciada pela disponibilidade de habitats naturais e
10 antrópicos, medida através de técnicas de sistemas de informações geográficas (SIG)
11 aplicadas em um mapa digital recente da cobertura vegetal e uso do solo da área de estudo
12 (Silva et al. 2011). A mesma técnica de modelagem também foi utilizada para gerar projeções
13 espaciais da abundância das espécies sobre a paisagem na área de estudo com base na
14 disponibilidade de habitats. Esses resultados poderão ser utilizados para informar políticas e
15 ações de conservação, assim como decisões de manejo.

Tabela 1. Aves de rapina diurnas estudadas. A nomenclatura científica segue Remsen et al. (2014).

Família	Espécie	Nome em inglês
Cathartidae	Urubu-de-cabeça-vermelha (<i>Cathartes aura</i>)	Turkey Vulture
	Urubu-de-cabeça-amarela (<i>C. burrovianus</i>)	Lesser Yellow-headed Vulture
	Urubu-de-cabeça-preta (<i>Coragyps atratus</i>)	Black Vulture
Accipitridae	Gavião-belo (<i>Busarellus nigricolis</i>)	Black-collared Hawk
	Gavião-preto (<i>Buteogallus urubitinga</i>)	Great Black Hawk
	Gavião-de-rabo-branco (<i>Geranoaetus albicaudatus</i>)	White-tailed Hawk
	Gavião-caboclo (<i>Buteogallus meridionalis</i>)	Savanna Hawk
	Gavião-caramujeiro (<i>Rosthramus sociabilis</i>)	Snail Kite
	Gavião-carijó (<i>Rupornis magnirostris</i>)	Roadside Hawk
Falconidae	Caracará (<i>Caracara plancus</i>)	Southern Crested-Caracara
	Falcão-de-coleira (<i>Falco femoralis</i>)	Aplomado Falcon
	Quiriquiri (<i>Falco sparverius</i>)	American Kestrel

Figura 1. Gavião-belo (*Busarellus nigricollis*) em lagoa no Pantanal próximo à Corumbá, MS.

Figura 2. Gavião-caramujeiro (*Rostrhamus sociabilis*) no Pantanal próximo à Corumbá, MS.

Capítulo 1

Modeling the abundance of unmarked animal populations: accounting for imperfect detection and other sources of zero inflation

Abstract

Inference and estimates of abundance are critical for quantifying population dynamics and impacts of environmental change. Yet imperfect detection and other phenomena that cause zero inflation can induce estimation error and obscure ecological patterns. Recent statistical advances provide an increasingly diverse array of analytical approaches for estimating population size to address these phenomena. We examine how detection error and zero-inflation in count data of unmarked individuals inform the choice of analytical method for estimating population size. We review two established (GLMs and distance sampling) and nine emerging methods that use N -mixture models (Royle-Nichols model, and basic, zero-inflated, temporary emigration, beta-binomial, generalized open-population, spatially explicit, single-visit and multispecies) to estimate abundance of unmarked populations, focusing on their requirements and how each method accounts for imperfect detection and zero inflation. Methods differ in sampling design requirements (e.g., count vs. detection/non-detection data, single vs. multiple visits, covariate data), and their suitability for a particular study will depend on the characteristics of the study species, scale and objectives of the study, and financial and logistical considerations. Researchers should evaluate these differences when designing studies to use funds, time and effort efficiently.

Key-words: abundance estimation, count data, detection, distance sampling, hierarchical model, multispecies abundance model, N -mixture model, population size, zero inflation

Resumo

Inferências e estimativas de abundância são críticas para quantificação de dinâmicas populacionais e impactos de mudanças ambientais. Contudo, a detecção imperfeita e outros fenômenos que causam inflação de zeros podem induzir erros de estimativas e dificultar a

1 identificação de padrões ecológicos. Avanços estatísticos recentes propiciam uma gama cada
2 vez maior de métodos analíticos de estimativa de tamanho populacional para lidar com esses
3 fenômenos. Neste estudo examinamos como a consideração de erros de detecção e a inflação
4 de zeros em dados de contagens de indivíduos não marcados pode informar na escolha do
5 método analítico apropriado para estimativas populacionais. Revisamos dois métodos já bem
6 estabelecidos (modelos lineares generalizados [GLMs] e amostragem de distância [*distance*
7 *sampling*]) e nove métodos emergentes que usam modelos hierárquicos baseados em misturas
8 (N-*mixture*; modelo de Royle-Nichols [RN], e N-*mixture* básico, zero inflacionado,
9 espacialmente explícito, visita única, e multiespécies) para estimar a abundância de
10 populações não marcadas, com foco nos seus pré-requisitos e em como cada método lida com
11 a detecção imperfeita e inflação de zeros. Os métodos diferem nos pré-requisitos de desenho
12 amostral (e.g., dados de contagens vs. dados de detecção/não-detecção, visita única vs. visitas
13 múltiplas, dados de covariáveis), e a sua adequabilidade para uma determinada investigação
14 vai depender das características da espécie em questão, da escala e objetivos do estudo, e
15 considerações financeiras e logísticas. Pesquisadores devem avaliar essas diferenças ao
16 planejarem estudos para que verbas, tempo e esforço sejam utilizados com eficiência.

17
18 **Palavras-chave:** estimativas de abundância, dados de contagens, detecção, *distance*
19 *sampling*, modelo hierárquico, modelo de abundância multiespécies, modelo N-*mixture*,
20 tamanho populacional, inflação de zeros

22 **Introduction**

23 Inference and estimates of abundance are critical for quantifying population dynamics and
24 the impacts of environmental change. Conducting a census (i.e., counting all individuals) of
25 almost any wild animal species is usually not possible. As a result, researchers have often
26 used relative abundance (i.e., the count itself or density) or an index of abundance (e.g.,
27 individuals detected per unit effort) as surrogates for population size (Buckland, Marsden &
28 Green 2008). Traditional approaches to population size estimation usually adopt sampling
29 designs that attempt to control for the factors influencing detection of individuals (e.g.,
30 observer, time of day, weather, etc.), but these approaches have limited ability to incorporate

1 the survey-, site-, and species-level processes that differentially affect the detection of species
2 or individuals (Iknayan *et al.* 2014). As such, it is common for the resulting counts to include
3 a disproportionate number of absences (i.e., many zeroes), a circumstance called “zero
4 inflation” (Martin *et al.* 2005).

5 Imperfect detection and zero inflation in count data have been increasingly discussed
6 in the ecological literature over the past decade (MacKenzie *et al.* 2002; Martin *et al.* 2005;
7 Royle & Dorazio 2008). When unaccounted for, both can introduce considerable estimation
8 error and obscure important ecological patterns (Wenger & Freeman 2008). For example,
9 models that generate so-called “detection-naïve” estimates of abundance, such as a Poisson
10 regression or a Generalized Linear Model (GLM) with a Poisson error distribution, perform
11 poorly in the presence of detection error (Sólymos, Lele & Bayne 2012). Furthermore, some
12 environmental factors that influence population size (e.g., canopy height or understory
13 density) and population size itself may also affect detection (Tanadini & Schmidt 2011;
14 Sólymos *et al.* 2012). Recognizing that perfect detection is rare in ecological data has led to
15 the development of statistical methods to account for detection error in counts of unmarked
16 populations (i.e., when animals are not individually identified) that formally accommodate
17 the detection process (Buckland *et al.* 2001; Royle & Dorazio 2008).

18 Here we review how detection error and zero inflation in count data of unmarked
19 individuals inform the choice of analytical methods for estimating the size of unmarked
20 populations. We begin by describing the sources of variation and types of zeroes that
21 frequently arise in count data. Then we review commonly used and recently developed
22 methods to model abundance of unmarked populations. We focus on how each method
23 accounts for imperfect detection and zero inflation. Finally, we discuss the performance and
24 sampling design requirements of these methods in the context of surveying and counting

unmarked populations. Our goal is to make recent statistical advances accessible for ecologists who wish to estimate population size.

Causes of variation and types of zeroes in count data

Variation in count data results from several distinct processes and understanding them is important to estimate abundance accurately (Martin *et al.* 2005). The number of individuals counted in a survey depends on the underlying (true) abundance of individuals and on their detectability. True abundance may vary among sites or sampling periods as a result of multiple ecological processes, including climatic variation, seasonal or environmental gradients, metapopulation dynamics, species interactions, and density dependence. Identifying these processes and understanding their relative importance is a common goal of research programs.

Detectability, either failing to detect an individual or misidentifying it, has species, individual, survey, and ecological underpinnings. Differences in species traits, such as conspicuousness, behavior, life history and rarity, can affect detection (Iknayan *et al.* 2014). In addition, individual traits, such as sex, age, or distance to the observer, are also important causes of non-detection. Detectability also varies due to survey-specific factors, such as effort, observer, weather, sampling method, or time of day or year. It can vary among sites, due to factors that influence visual or auditory detection regardless of observer, such as habitat structure or noise (Alldredge, Simons & Pollock 2007). Importantly, detection is also affected by the underlying abundance (Tanadini & Schmidt 2011). In this context, a non-zero count is the outcome of an underlying non-zero abundance filtered through the detection process. However, variability in count data can also be due to misidentification (i.e., a false positive). Generally, researchers agree (and hope) that false negatives are much more

frequent than false positives, as there are considerably fewer studies examining the latter circumstance (but see Royle and Link 2006, McClintock et al. 2010).

Counts that result in zeroes, on the other hand, can arise from several different situations (Fig. 1). Zeroes due to ecological processes are true zeroes, in the sense that species are absent from the site (Fig. 1a). In many investigations this is interpreted to be a consequence of unsuitable habitat or competitive exclusion (Martin *et al.* 2005). However, a second type of true zero is induced by demographic stochasticity (Fig. 1a), when species fail to saturate all suitable habitats due to random local extinctions and dispersal limitation (Martin *et al.* 2005). Species rarity can increase the frequency of this type of zero in count data (Fig. 1b), due to a higher probability of local extinctions when populations are small.

Additional true zeros can also occur when the occupancy pattern and local abundance distribution of a species are the outcome of distinct processes, such as habitat selection operating at different spatial and temporal scales (Wenger & Freeman 2008). Consider, for example, animals that specialize in a spatially restricted resource, such as a hawk that mainly consumes aquatic prey. Except during dispersal and migration, this species is likely to be found only near rivers, lakes, ponds and other water bodies; that is, its potential occupancy is dependent on the presence of these habitats. Regional surveys may include sampling units in or near such habitats, but will also likely include dry sites where the species will be absent. In the wet sites, the abundance of the species might be predictable by other environmental factors (e.g., proportion of natural vegetation area, degree of fragmentation, land use, etc.). Such factors may favor the species in the dry site, but it will be absent because there is no body of water. Large numbers of these absences, more common in sparsely than in widely distributed species (Fig. 1a, non-occupancy true zeroes), induce error in analysis and confound interpretation because models will attempt to estimate abundance of the species in an environment where it does not occur. However, this “potential occupancy” process should

not be strictly equated with occupancy in the sense that wet sites are always occupied, because it is possible for the abundance to be zero in the wet sites due to other environmental factors being unfavorable. Sampling only sites that are potentially occupied avoids this non-occupancy zero inflation, as does incorporating the factor determining occurrence of the species in models (e.g., adding presence of water bodies as a covariate for the above example; the covariate will have a strong effect on abundance such that when it has value 0, the expected abundance will be essentially zero). The latter approach is not achievable when the required knowledge is not available, or when conducting multispecies surveys (Wenger & Freeman 2008; Joseph *et al.* 2009).

False zeros, on the other hand, result from the observation process and can arise in two ways: (1) the individual may be present at the site but be undetected by the observer (Fig. 1b), which is commonly called "detection error" or "imperfect detection" (MacKenzie *et al.* 2002; Royle & Dorazio 2008); and (2) an individual of a mobile species with a large home range may regularly use a site but be absent from it at the time of survey, because it is visiting part of its home range outside of the sample unit. The latter may commonly occur if the sampling area is small and/or the length of visit is short relative to the movements of the species, and it is often termed "temporary emigration" or "temporary absence" (Fig. 1c, Tyre *et al.* 2003, Chandler *et al.* 2011). Both causes of false absence are likely to occur during animal surveys, because many species have large home ranges or are undetected due to cryptic behavior and camouflage. As discussed above for nonzero observations, detection is also influenced by the type of habitat where an observation is made, time of day when it takes place, weather, distance to the observer, and variation between observers (Buckland *et al.* 2001; Alldredge *et al.* 2007; Iknayan *et al.* 2014).

Modeling methods for estimating abundance of unmarked animal populations

In this section we review established and emerging methods to model abundance of unmarked populations, and focus on how they handle imperfect detection and zero inflation (Figure 2, Table 1). These methods can be used to address several different ecological questions regarding inference and estimates on detection, populations and communities (Table 2). We start with Poisson and negative-binomial GLMs, which are simple and widely used methods for modeling non-normal data (including counts) that generally disregard detectability. Next, we describe distance sampling methods that model detectability based on the distance between the observer and the animal. We then discuss hierarchical (N -mixture) models, which estimate detectability based on multiple-visits, followed by the single-visit N -mixture models that employ covariate data to model detection instead of multiple visits. Finally, we describe multispecies N -mixture abundance models that account for detectability and make inference about the number of species not detected during surveys in the study region. They can also be used to estimate community measures such as species richness, diversity and similarity.

Established methods

Poisson and negative-binomial GLMs

Abundance of unmarked populations has often been estimated from count data using Poisson GLMs (Nelder & Wedderburn 1972; Zuur *et al.* 2009). A GLM is a generalization of the linear regression that allows the response variable to have error distributions other than Gaussian; in this case, it assumes that the error term follows a Poisson or negative binomial distribution. Variation is described by environmental variables assigned as covariates using a log link. The choice of distribution arises from assumptions of how organisms are distributed in space in a homogeneous landscape. Potential departures from randomness arise as a result

of ecological heterogeneity and are explained by covariates. The negative binomial GLM allows the error distribution to vary independently of the mean, and has been suggested as an alternative to account for extra Poisson variation (Zuur *et al.* 2009). It is also used when there is violation of independence of observations (e.g., individuals occurring in aggregations).

GLMs are frequently used with count data because they are easy to build, can be applied to the simplest count datasets (e.g., n sampling sites each visited once during a sampling period), work in both frequentist and Bayesian frameworks (Bayesian estimates under a vague [i.e., uninformative] prior will be numerically close to maximum likelihood estimates [Kéry and Schaub 2012]), and are available in many statistical platforms.

GLMs are appropriate tools for drawing inference on the factors affecting the relative abundance of a species, provided such factors do not also strongly influence detectability. However, when the objective of the study is to obtain a precise estimate of the abundance, or to draw inference on effects acting upon the actual abundance, GLMs cannot account for departures from the error distribution resulting from excessive true or false zeroes (Table 2). Consequently, if the data analyzed do contain this "additional" variation, use of the Poisson and negative binomial GLMs will be inadequate (Welsh *et al.* 1996; Joseph *et al.* 2009). Data transformations are ineffective in normalizing zero values because the excessive zeros are simply replaced by an equally frequent non-zero value (Martin *et al.* 2005). An alternative approach used in many studies is to truncate data sets, reducing or even eliminating the zero values before the GLM analysis. This can compromise the estimation of parameters, because some of the zeros removed will likely be true zeros and their corresponding covariate values will be ignored (Joseph *et al.* 2009).

1 *Distance sampling*

2 This is a group of methods in which distances from the survey points or lines to the clusters
3 (or groups) of detected individuals are recorded, and used to estimate density or abundance
4 (Buckland *et al.* 2001, 2008). All individuals at zero distance from the sampling point or
5 transect are assumed to be detected, and the detection probability (p) is modeled to decrease
6 with increasing distance from the point or transect. The distribution of distances recorded
7 with every sighting is used to estimate a detection function (the proportion of individuals
8 detected at different distances), which in turn allows estimation of density and abundance
9 (Buckland *et al.* 2001). Thus, distance sampling methods accommodate false zeroes
10 originating from the detection process under the hypothesis that detectability is primarily
11 related to the distance between animals and the observer. A major advantage of the distance
12 sampling methods is that they do not require repeated sampling of sites over time to estimate
13 p , as opposed to most N -mixture models (see below).

14 There are six central assumptions of the basic forms of distance sampling: (1) objects
15 on the line or point are detected with certainty; (2) objects do not move in response to the
16 observer during a survey or before detection (i.e., they are detected at their initial locations);
17 (3) distance measurements are exact; (4) the position of detected individuals is independent
18 of the survey point or line; (5) cluster sizes are recorded without error; and (6) detections are
19 independent events. Violations of these assumptions may result in biased estimates
20 (Buckland *et al.* 2001, 2008). Distance sampling data are frequently analyzed with the free
21 program Distance, which also provides guidelines for survey design (Thomas *et al.* 2010).

22 Considerable effort has been focused on modeling covariate effects on p in distance
23 sampling methods (Marques & Buckland 2003; Marques *et al.* 2007) compared to
24 incorporating covariate effects on abundance, despite the fact that the objective of most
25 studies is to understand the processes that influence variation in abundance. Royle *et al.*

(2004) addressed this issue using a modified distance-sampling, hierarchical model that treated counts as a function of p and site-specific abundance (N_i , at sampling unit i [points or line segments]). N_i was modeled as a Poisson (or negative-binomial) random effect that could be related to covariates through a link function. Site-specific abundances were integrated from the likelihood function, while parameters of the count distribution (e.g., mean $[\lambda]$ for the Poisson and negative binomial distributions, and the overdispersion parameter $[\alpha]$ for the later) were estimated from the data (Royle *et al.* 2004). This method is a hybrid between distance sampling and N -mixture models. The approach was extended in Sillett *et al.* (2012) to include covariate effects on the detection function in a similar manner. These models are freely available in the *Unmarked* package (Fiske & Chandler 2011) for the free statistical software R (R Development Core Team 2014). Other hierarchical distance sampling approaches for unmarked populations include Hedley & Buckland (2004) and Niemi & Fernández (2010).

Emerging methods

Hierarchical (N-mixture) models for multiple visits

Hierarchical models handle variation in the observed data as a result of explicit *observation* and *state process* components (Royle & Dorazio 2008). Detection error is incorporated in the observation component, while the state process component incorporates the underlying ecological process (i.e., abundance or occupancy). This class of models includes approaches that generally require temporally-replicated surveys (i.e., repeated measures) conducted at multiple locations, but a variant of these models can be applied to single-visit data sets as described in the next section.

The repeated measures design to allow estimation of p was initially applied by MacKenzie *et al.* (2002) to detection/non-detection data in occupancy models to estimate the

1 proportion of sites occupied (i.e., contain ≥ 1 individual). In these models p can be modeled
 2 as a constant or as a function of known covariates that can be site- or survey-specific. This
 3 includes abundance-induced variation in detectability, which led Royle and Nichols (2003) to
 4 propose a model to estimate abundance from observations of detection/non-detection
 5 (hereafter, the RN model). In the RN model, the detection frequencies for each i site
 6 (obtained from the repeated j counts) are assumed to follow a binomial distribution with
 7 sample size j and parameter p_i , which in turn depends on the unknown N_i , a random variable
 8 with a specified distribution (e.g., Poisson). Thus, the model assumes that site-specific
 9 detection probabilities are functionally dependent on local abundance. In other words, it
 10 obtains information about the local abundance distribution directly from the apparent
 11 heterogeneity in p among sites induced by variation in abundance (Royle & Dorazio 2008).
 12 Structurally, the model is analogous to classical generalized random effect models, with N_i as
 13 the random effect. Measurable variables that are thought to influence detection and
 14 abundance may be added to the model as covariates using a link function (e.g., log for the
 15 Poisson in the abundance portion). The RN model incorporates false zeroes from detection
 16 error and true zeroes from abundance. While it is not built with an explicit occupancy
 17 probability (ψ), this parameter can be derived by defining unoccupied sites to have a zero
 18 detection probability (as a result of zero abundance), and then $1-\psi$ becomes the point mass at
 19 zero abundance (Royle & Nichols 2003).

20 Unmarked populations are a promising area of application of the RN model. For
 21 example, many species occur in low densities and are territorial, favoring occupancy
 22 sampling instead of counts. However, the premise of functional dependence between
 23 detection probability and local abundance may not be a reasonable assumption in some
 24 situations, such as extremely rare or highly territorial species. In such cases, density might be
 25 so low that local abundance (N_i), given presence, is essentially constant (i.e., $=1$) and thus

1 heterogeneity in apparent detection probability among sites is null or negligible, undermining
2 the fundamental proposition of binomial detection in the RN model.

3 Obviously, not all species are so rare that only occupancy sampling is possible and
4 many datasets are composed of counts. The basic N -mixture model for count data combines a
5 binomial GLM (for the observed counts) and a standard model (Poisson or negative
6 binomial) for N_i . It assumes that the population sampled is closed during the sampling period
7 with respect to mortality, recruitment, and movement (Royle 2004b). It also assumes that
8 detections at a site are independent, and that all individuals recorded at a given site and time
9 have the same detection probability (Royle 2004b). Counts at site i are regarded as a binomial
10 process dependent upon p (*i.e.*, the observation process) and N_i , a Poisson (or negative-
11 binomial) random variable (*i.e.*, the underlying state process). Additional explanatory
12 variables can be included in both the abundance and the detection models using standard
13 generalized linear modeling techniques. The method generates parameter estimates of the
14 abundance distribution across sites (*e.g.*, λ in the case of a Poisson distribution, or λ and α for
15 negative binomial) that allow evaluation of temporal changes or geographic comparisons.
16 Total abundance can be estimated posteriorly if the sample units are of known area (Royle
17 2004b). These models yield estimates of p , thus accounting for detection error and the
18 resulting false zeros (Royle 2004b). Estimates can be generated with either frequentist
19 (maximum likelihood estimation) or Bayesian approaches (Kéry 2008; Kéry & Schaub
20 2012). This type of model can be fit using the *Unmarked* R package (Fiske & Chandler 2011)
21 for frequentist, or by Bayesian methods with WinBUGS (Lunn *et al.* 2000), OpenBUGS
22 (Lunn *et al.* 2009) or Jags (Plummer 2003).

23 The Poisson and negative binomial distributions are adequate to model abundance at
24 occupied sites in the N -mixture, but they perform poorly when the data include a large
25 number of true zeros. This can occur when unoccupied sites are sampled (Wenger & Freeman

2008; Joseph *et al.* 2009). Extensions of the N -mixture models were proposed to accommodate excess true zeroes, in addition to the false zeros from detection error, by employing zero-inflated mixture distributions such as the zero-inflated Poisson (ZIP) to model abundance and potential occupancy simultaneously (Wenger & Freeman 2008; Joseph *et al.* 2009). The ZIP distribution is a mixture of a Poisson distribution, with a rate or average parameter (λ) and a Bernoulli distribution with a parameter (ψ) for the probability that a species is potentially present (i.e., the potential occupancy – different from the true occupancy because even when $\psi=1$ a site may still be unoccupied due to other factors acting upon the abundance process [i.e., the Poisson zeros]).

These mixture models allow three sources for zeroes in data – the false zeroes from detection error, and the true zeroes from potential occupancy and abundance. As in the original N -mixture, counts in site i are the result of a binomial process dependent on p and N_i . The latter is, in turn, a product of the potential occupancy process (dependent on ψ) in addition to the abundance process (dependent on λ). Covariates can be used for the detection, presence, or abundance terms with appropriate link functions, and the same covariate may be used for more than one process (e.g., percent forest cover for detection and abundance). Like the basic N -mixture model, use of other zero-inflated distributions, such as the zero-inflated negative binomial (ZINB), for modeling the abundance-potential occupancy portion is possible (Wenger & Freeman 2008; Joseph *et al.* 2009). However, this can often result in unrealistic parameter estimates despite good model fit, so should be used with caution (Joseph *et al.* 2009). Zero-inflated N -mixture models inherit the assumptions of the original N -mixture model – population closure, independence of observations and choice of error distribution.

Recent developments in N -mixture models focus on handling violations of assumptions or sampling requirements: (1) Chandler *et al.* (2011) developed a variation of the

N -mixture model to explicitly account for temporary emigration by adding a binomial zero-inflation level, whereby each individual is considered to be within the survey plot with probability ϕ (and $1-\phi$ is the probability of temporary emigration). Variation in ϕ can be modeled as a function of site and survey-specific variables, although often this variation will more likely be a result of disparity between the sizes of survey plots relative to the species' home range (Chandler *et al.* 2011); (2) Martin *et al.* (2011) developed a beta-binomial N -mixture model to account for non-independent (correlated) detection of individuals. This can occur when the behavior of an animal affects the probability of detection of other individuals by the observer (e.g., when singing behavior in birds and amphibians elicits a response from a neighboring individual). The binomial distribution in the observation model (with parameters N and p) is replaced by the beta-binomial (with N , p and the correlation parameter ρ); ρ increases with stronger correlation (Martin *et al.* 2011).

Dail and Madsen (2011) proposed a Generalized N -mixture method that can be used to formally test the closure assumption through estimation of parameters of population dynamics. When applied to data from an open population (e.g., annual counts), the model estimates arrival rate of new individuals (γ , which includes both births and immigrants) and survival probability (ω), which can in turn be used to estimate abundance while accounting for imperfect p . In addition, because the model does not assume a closed population, it is not necessary for the repeated visits to be performed within a single season, and so multiple-season datasets with a single visit per season can also be analyzed (e.g. the North American Breeding Bird Study). Description of the generalization procedure is extensive, so we refer readers to the original article for details (Dail & Madsen 2011). The model is freely available in the *unmarked* R package (Fiske & Chandler 2011).

Yet another recent development of N -mixture models for unmarked populations is the spatially explicit density model (Chandler and Royle 2013), which is an adaptation of spatial

capture-recapture (SCR) models for estimating density of marked individuals (Efford 2004; Borchers & Efford 2008). SCR models estimate density or population size based on estimation of the activity centers of individuals in the sampled area from encounter histories using capture/recapture data. Activity centers, which cannot be directly observed, are the spatial average of an individual's locations during a time period. The model uses the information from the spatial coordinates of traps with captured individuals to determine the locations of the activity centers, while capture probability (the equivalent of detection probability for capture/recapture data) is regarded as a function of the distance between survey (i.e., trap) locations and activity centers, similar to the detection function in distance sampling (Buckland *et al.* 2001). The spatially explicit density model has a structure similar to the SCRs, but uses the spatial correlation (σ) in temporally replicated counts to estimate the number and location of the activity centers instead of individual identification. Because spatial correlation between counts is required, sample locations need to be in close proximity to one another relative to the size of a home range to allow individuals to be detected at multiple locations over the repeated visits. An interesting aspect of the method is that, unlike most other approaches for estimating abundance or density, spatial correlation is not viewed as an obstacle for inference, but instead informs estimation of distribution and population size (Chandler & Royle 2013).

Single visit N-mixture models

The multiple visit methods described above allow more accurate estimates of abundance than so-called “detection-naïve” estimators (e.g., GLMs) by using variation in counts between visits to adjust for detection error. This, however, is not the only way to model detectability with *N*-mixture models. In both presence/absence and count data, detection error can be

accounted for using only a single visit to a site if covariates that affect detection and abundance are available (Lele, Moreno & Bayne 2012; Sólymos *et al.* 2012).

The binomial–ZIP mixture model for analyzing single visit count data in the presence of zero inflation and detection error replaces the need for repeated visit data and the assumption of population closure used in the multiple visit approaches with the requirement of non-overlapping sets of covariates that affect detection and abundance (Sólymos *et al.* 2012). The detection and abundance covariate sets need to differ by at least one continuous covariate (i.e., they can share covariates provided that at least one continuous covariate is unique to either set). As in the multiple visit zero inflated N -mixture approach, the model is built with detection, abundance and zero inflation terms, and their respective error distributions, link functions, and covariates. Direct maximization of the likelihood function can lead to considerable confounding between the zero-inflation parameter and the intercept parameter in the detection model, so conditional likelihood is employed. This likelihood conditions on the zero-inflation parameter (representing, for example, potential occupancy) to estimate the detection and abundance parameters; that is, it separates the parameter space and thus reduces the extent of confounding (Sólymos *et al.* 2012).

Like the multiple visit binomial–ZIP mixture model described in the previous section, the single visit N -mixture model includes an ecological process level, an observation level, and an additional zero-inflation level. Thus, it can account for detection error and other forms of zero-inflation, such as those derived from non-occupancy or temporary absence. The method is implemented in the R package *detect* (Sólymos, Moreno & Lele 2013).

Multispecies N-mixture abundance models (MSAMs)

Although abundance is a valuable attribute for evaluation and comparisons, parameters such as species richness, diversity, and similarity are also important to understand community-

level variability (Dorazio & Royle 2005; Dorazio *et al.* 2006; Yamaura *et al.* 2012; Iknayan *et al.* 2014). Yet, methods for estimating these community metrics, many of which require measures of species abundance, have remained separate until recently. Multispecies abundance models (MSAMs) are an extension of multiple visit single-species abundance models that analyze the detection histories (i.e., the repeated counts) of all species encountered. The detection histories are used to inform the estimation of diversity, richness and derived metrics, including the number of species that were present in the community but were not detected at any site – a measure that is useful for communities dominated by rare species (Dorazio & Royle 2005; Iknayan *et al.* 2014). MSAMs are still in their infancy, so there are very few applications to date (Yamaura *et al.* 2011, 2012; Chandler *et al.* 2013). However, MSAMs draw much of their structure from multispecies occupancy models (MSOMs), which have a longer history of use (see Iknayan *et al.* 2014 for a review).

Initial MSAMs were developed by combining two different modeling frameworks based on detection/non-detection data (Yamaura *et al.* 2011): (1) the RN model for estimating abundance (Royle & Nichols 2003) and (2) an MSOM that allows for estimation of species richness and community composition at a given site by accounting for both undetected species and variability in occupancy and detectability among species (Dorazio & Royle 2005; Dorazio *et al.* 2006). The model requires repeated visits at multiple sites to collect detection/non-detection data for each species. These detection histories are then linked to species abundance based on the RN model, and variation in detectability and abundance across sites can be modeled as a function of site-specific covariates for each species. Further development of MSAMs allow use of counts of individuals instead of detection/non-detection data (Yamaura *et al.* 2012), as in single species *N*-mixture models for count data.

For well-detected species, model parameters including covariate coefficients can be independently estimated, but this is not the case for rare species due to insufficient data. The

MSAM has an additional hierarchical level that treats each parameter as an independent, normally-distributed random effect across species; that is, the value of each parameter for each species is assumed to be drawn from a normal distribution with mean and standard deviation that represent the mean response across species and the standard deviation among species (Yamaura *et al.* 2011; Iknayan *et al.* 2014). The mean and standard deviation community parameters are termed hyper-parameters.

Data-augmentation is used in MSAMs to estimate the number of species present in the community but not detected at any site. In addition to the ecological process (i.e., abundance) and observation (i.e., detection) levels already present in single-species hierarchical models, the multispecies approach has a supercommunity (data-augmentation process) level, with parameter Ω . The supercommunity comprises the observed species (s) and an arbitrary but known number (m) of unobserved species. The inclusion rate (Ω) is the probability a species that belongs to the supercommunity is sampled (Royle & Dorazio 2008; Iknayan *et al.* 2014). In the data-augmentation approach, m all-zero detection histories are added to those of the s observed species, and used as input data for the model. An indicator variable that separates the data into species present (detected or not) and those not present in the community (and hence not detected) is also added to the model (Royle & Dorazio 2008). This variable is indexed by Ω , which is the parameter estimated. The number of species in the region (i.e., gamma diversity) is obtained by multiplying the estimate of Ω by the sum of s and m .

Both MSAM models (detection/non-detection and count-based) accommodate, but do not require, the inclusion of site and survey-specific covariates and also allow for estimation of community-level metrics derived from richness, such as diversity and similarity indices like species-accumulation curves (Royle & Dorazio 2008; Iknayan *et al.* 2014). The supercommunity level of the model, by modeling the presence or absence of each species,

1 already handles the zero-inflation derived from non-occupancy. Moreover, use of ZIP or
2 ZINB distributions for the ecological process level should be possible to account for
3 additional zero-inflation (*e.g.*, temporary absence), but to our knowledge have not yet been
4 implemented. Because data-augmentation requires estimation of the parameters by Markov
5 chain Monte Carlo (MCMC), current implementation of multispecies abundance models is
6 mostly restricted to Bayesian inference programs such as WinBUGS (Lunn *et al.* 2000),
7 OpenBUGS (Lunn *et al.* 2009) or Jags (Plummer 2003).

8 **Discussion**

10 In this section we summarize and compare the performance of the emerging methods for
11 estimating abundance described above, focusing on estimation bias and sample size
12 requirements. We conclude by discussing study design and how different analytical methods
13 are best suited for particular situations.

14 *Method performance*

16 Detection-based estimation approaches generally performed well when evaluated against
17 simulated data sets (Table 3). They typically estimated population size without strong bias,
18 except in scenarios when detection probability was low and few sites were sampled a small
19 number of times. An encouraging result from the RN model, which likely applies to the other
20 methods, is that bias from small sample size can be countered by increasing the number of
21 visits to each site (from 3 to 5-10) or if the species has a high detection probability ($p \geq 0.3$,
22 Royle & Nichols 2003). When sample size was small, which sometimes skewed the mean of
23 the abundance estimator, the median and mode were close to their true values (Royle 2004b).
24 Similarly, in the spatially explicit density model, low spatial correlation in counts ($\sigma = 0.5$)
25 results in a biased mean of population size estimates (5-10%), but their mode is unbiased

(Chandler & Royle 2013). Simulations with the Generalized N -mixture model showed that population dynamics were falsely detected at very low rates ($<1\%$) in closed population scenarios ($[\gamma, \omega] = [0, 1]$), suggesting the model performs adequately as a test of the closed-population assumption (Dail & Madsen 2011).

Few field studies have applied multiple estimation methods to compare their relative performance. Abundances were higher when estimated with N -mixture models compared to estimates derived from territory mapping of birds (Kéry, Royle & Schmid 2005) and from distance sampling transects of desert tortoises (Zylstra, Steidl & Swann 2010), but not compared to direct observations of lizards (Doré *et al.* 2011). Precision (i.e., confidence intervals) of estimates varied among methods; estimates from N -mixture models had higher precision compared to other methods for lizards (Doré *et al.* 2011) but not for tortoises (Zylstra *et al.* 2010). Couturier *et al.* (2013) extended the tortoise studies to compare abundance estimates from capture-recapture, distance sampling, and N -mixture models, conducted simulations to assess bias between capture-recapture and N -mixture models, and computed a power analysis to evaluate the ability of the three methods to detect changes in abundance. The capture-recapture method resulted in abundance estimates 1.75 and 2.19 times greater than distance sampling and N -mixture models, respectively. Simulations showed that the N -mixture models resulted in estimations that were biased high when detection probabilities were small (<0.5), whereas capture-recapture estimations were unbiased. That the N -mixture method showed less precision than distance sampling and capture-recapture in a species with low detectability (Couturier *et al.* 2013) is not surprising, given the additional information provided by distance measurements and individual marking. None of the methods were precise enough to detect small ($< 1\%/year$) population changes (Couturier *et al.* 2013). Martin *et al.* (2011) applied binomial and beta-binomial N -mixture models (both with a Poisson abundance distribution) in a Bayesian approach to aerial survey

1 data of manatees, in which correlated surfacing behavior caused non-independent detection
2 of individuals, and assessed their fit using posterior predictive distributions (Gelman, Meng
3 & Stern 1996). They found that the former model did not fit the data, whereas there was no
4 evidence of lack of fit for the latter.

6 *Considerations for study design and choice of analytic framework*

7 The modeling approaches reviewed in this paper can be used to investigate several ecological
8 questions, not only about population size and the factors that affect it, but also about
9 detection and even the community (see Table 2 for examples). Because they do not explicitly
10 model detection, Poisson and negative binomial GLMs (as described above) should only be
11 used to address questions about the relative abundance (i.e., the product of abundance and
12 detection) of unmarked populations, such as identifying factors that may cause different
13 patterns among areas or periods.

14 Given that detection error is pervasive in sampling of unmarked animal populations,
15 we focus the remainder of the Discussion on the methods that incorporate estimation of
16 detection probability (Figure 2, Tables 1 and 2). Estimation methods can be divided into
17 those that require one visit and those that require multiple visits (Figure 2, Table 1). With the
18 likely exception of surveys of insects and other invertebrates, multiple visit surveys should
19 typically take place on different days to maintain sample independence. Visiting a site on
20 several dates within a sampling season increases travel costs and personnel time. For a given
21 budget, this will likely reduce the number of sites that can be surveyed, potentially decreasing
22 the generality of the study (Lele *et al.* 2012). This issue becomes especially important when
23 sampling species that occur in low densities, because surveying a large number of sites is
24 crucial to obtain enough non-zero observations for reliable population inferences. Tradeoffs
25 between the number of visits and number of sites surveyed must be considered carefully with

1 regard to the objectives of the study. Monitoring populations in small to moderately sized
2 areas may be a more likely scenario for use of multiple visit methods than regional-scale
3 studies. For the latter, single visit methods may be a cost-effective option. Below we first
4 discuss the single visit methods, and return to the multiple visit approaches later.

5 Single visit methods (Figure 2, Table 1) replace repeated visits with auxiliary data to
6 estimate detection probability. The most widely used single-visit method is distance
7 sampling, which assumes that the distance-to-observer measurements are made with minimal
8 error and that detection at the survey point or line is perfect (Buckland *et al.* 2001). In
9 practice, distances-to-observer can be difficult to accurately measure if surveys rely on aural
10 detections, or if surveys include a considerable proportion of fast-moving individuals (e.g.,
11 birds in flight). To illustrate, we describe encounter data for 10 common raptor species
12 detected during roadside strip-transects in open habitats in west-central Brazil (Dênes *et al.*
13 unpublished data). Eight of the 10 species had more than 20% of individuals detected in
14 flight, suggesting that a large proportion of the distance-to-observer measurements might not
15 be reliable for density estimation with distance sampling. Thus, it may be useful to conduct
16 an assessment of mode of detection (e.g., the ratio of flying vs. stationary or aural vs. visual
17 detections) when designing a study before deciding to adopt distance sampling; datasets in
18 which detections are frequently of non-stationary or calling individuals are probably better
19 suited for other methods.

20 Point or transect counts are commonly performed along roads, rivers or paths,
21 especially counts focusing on larger, highly mobile species (e.g., raptors, parrots, and some
22 waterfowl), due to ease of access and time and resource limitations (Buckland *et al.* 2008).
23 Many factors along such features can lead to atypical density, including an increased
24 frequency of perch sites (e.g., power and telephone posts and lines, fences, road-signs, etc.),
25 more food for scavenging species (i.e., road-kills), and increased edge habitats (Buckland *et*

al. 2008). Although this can present a problem for any analytical method when extrapolating over a larger region, distance sampling is particularly vulnerable because it relies so heavily on the spatial distribution of individuals in the vicinity of the sample point or line. Alternative strategies for placing sample units have been suggested to handle this problem, such as transects perpendicular to roads or paths (Buckland *et al.* 2008), but these strategies are not always feasible or logistically viable. In such situations, it might be better to replace distance sampling with an alternate detection-based method to model count data (Figure 2, Table 1).

The *N*-mixture method for single-visit count data (Sólymos *et al.* 2012) requires non-overlapping sets of covariates for detection and abundance. Most research and monitoring studies designed to compare abundance between different conditions or sampling periods are likely to collect detection and abundance covariates. For example, detection covariates often include time of day, weather, habitat, and observer, which are frequently available for most data sets. If, however, the proper covariates are not collected and modeled, abundance estimates will be inaccurate regardless of the number of sampling visits (Sólymos *et al.* 2012). Hence, the need to collect covariates to use the single visit approach can hardly be considered an objection to its use. When limited budget or sampling logistics preclude the use of the multiple-visit *N*-mixture or distance sampling methodologies, the single visit method accommodating detection error and zero inflation provides an interesting alternative.

Focusing on the number of occupied sample units using multiple visits instead of on the number of animals in each unit has been suggested to reduce the efforts and costs associated with monitoring (MacKenzie *et al.* 2002; Royle & Nichols 2003). The RN model follows this general approach to produce an estimate of population size (Figure 2, Table 1), and it is especially useful for situations where little information is available beyond detection/non-detection data (Royle & Nichols 2003). For example, detection of multiple individuals seldom occurs when monitoring of rare or very elusive species (with the caveat

that cases of extreme rarity can be a problem even for the RN method). When it is not possible to ensure that individuals are not counted more than once during a visit, reduction of the count data to detection/non-detection for use in the RN model may be a useful approach.

When reliable multiple visit count data are available, several N -mixture methods (Figure 2, Table 1) allow researchers to model not only abundance and detection but also additional phenomena, such as temporary emigration, non-independent detection of individuals, population closure (a basic premise of the multiple visit approach itself), and population dynamics parameters (i.e., arrival rate of new individuals [births and immigrants] and survival probability; Table 2). The versatility of this framework should encourage researchers to collect multiple visit count data whenever their research system and budget allow.

Recently, the use of single species models that adjust for imperfect detection in situations where communities are dominated by rare species, such as tropical rainforests, has been questioned due to their requirement for high detection or recapture probabilities, which are unlikely to be obtained for rare species (Banks-Leite *et al.* 2014). The multispecies N -mixture framework uses data from the entire sample (common and rare species) to inform a community-level distribution of detection and occupancy or abundance probabilities (via hyper-parameters) from which estimates for each species, including rare ones, are obtained. This “information sharing” allows data to be used more efficiently compared with single-species models, and individual estimates are improved (Iknayan *et al.* 2014). A great advantage of multispecies abundance N -mixture models, which to our knowledge currently exists only in the multiple visit framework, is the ability to combine abundance and richness estimates while explicitly incorporating observation error (i.e., imperfect detection) in count data (Figure 2, Table 1). However, this type of hierarchical model is relatively new, so its limitations and performance remain to be more widely evaluated. In addition, implementation

of the models is still complex and beyond the programming expertise of many potential users, despite the fact that example code and software are freely available on the Internet (Iknayan *et al.* 2014).

Conclusions

Population studies with the goals of informing conservation actions and management decisions need to rigorously estimate abundance and how it is influenced by multiple factors. We believe this involves recognizing that, regardless of observer expertise, count data are subject to detection error and multiple forms of zero inflation (Fig. 1). Thus, adopting a sampling scheme and analytical method that account for these phenomena is necessary to address most questions that involve drawing inference or obtaining estimates about population size (Table 2). Of the 11 kinds of analytical methods used to estimate population size we have reviewed (Table 1), eight can account for both imperfect detection and additional variation in population size in the forms of non-occupancy, temporary emigration, correlated detection and population dynamics. All eight have been developed within the past decade, and their efficacy is still under study (Table 3). We expect developments to continue in this important area of statistical ecology.

Methods for estimating population size vary in their degree of suitability for a research project, depending on the taxa sampled, whether surveys are composed of a single or multiple species, the availability and feasibility of collecting ancillary data, and the scale and the objectives of the study. Estimation methods can also impose differing financial and logistical costs, depending upon the requirement for repeated visits (Fig. 2, Table 1). Researchers should be aware of these differences when designing studies, so that limited funds and effort are spent efficiently.

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Table 1. Established and emerging methods for estimating abundance of unmarked animal populations, with associated data types and sampling requirements. p lists the strategy employed by each method to estimate detection probability (p). ZIF/other variation indicates the parameters estimated when accounting for zero inflation or other additional variation, where ψ is the potential occupancy probability, $1 - \phi$ is the probability of temporary emigration from the sample unit, ρ is correlation in detection of individuals, γ is arrival rate of new individuals, ω indicates survival probability, σ is the spatial correlation in counts, and Ω is the probability that a species is present in the supercommunity. Covariate handling indicates terms (or levels) that accept covariates in each model.

Method	Data type	Sampling requirements	p	ZIF/other variation	Covariate handling	Examples
GLMs (Poisson, NB)	Count	Single visit surveys	None	-	Relative abundance	Nelder and Wedderburn (1972), Zuur et al. (2009)
Distance sampling	Count	Single visit surveys and distance measurements	Distance-to-observer	-	Detection, abundance	Buckland et al. (2001), Royle et al. (2004)
RN model	Detection/non-detection	Multiple within-season surveys	Repeated surveys	ψ	Abundance, detection and ZIF	Royle and Nichols (2003, Royle and Dorazio (2008)
Basic N -mixture	Count	Multiple within-season surveys	Repeated surveys	-	Abundance, detection	Royle (2004), Royle and Dorazio (2008), Dail and Madsen (2011)
Zero-inflated N -mixture	Count	Multiple within-season surveys	Repeated surveys	ψ	Abundance, detection and ZIF	Wenger and Freeman (2008), Joseph et al. (2009)
Temporary emigration N -mixture	Count	Multiple within-season surveys	Repeated surveys	ϕ	Abundance, detection and temporary emigration	Chandler et al. (2011)
Beta-binomial N -mixture	Count	Multiple within-season surveys	Repeated surveys	ρ	Abundance, detection and detection correlation	Martin et al. (2011)
Generalized N -mixture	Count	Multiple surveys (not necessarily within seasons)	Repeated surveys	γ, ω	Abundance, detection, arrival and survival rates	Dail and Madsen (2011)
Spatially explicit density model	Count	Multiple within-season surveys, spatially referenced counts	Spatial correlation in repeated counts	σ	Abundance, detection and spatial correlation	Chandler and Royle (2013)

Single visit N -mixture	Count	Single visit surveys and abundance and detection covariates	Covariates	ψ	Abundance, detection and ZIF	Sólymos et al. (2012)
Multispecies N -mixture	Detection/non-detection or Count	Multiple within-season surveys	Repeated surveys	Ω	Abundance, detection and ZIF	Yamaura et al. (2011, 2012), Chandler et al. (2013)

Table 2. Common questions asked in ecological studies, and the established and emerging methods for estimating abundance of unmarked animal populations that can be used to address them.

Questions often asked in ecological studies	#	Method	Appropriate to investigate #
Detection			
How is detection of individuals affected by environmental variables?	1	GLMs (Poisson, NB)	3
Is detection of individuals correlated?	2	Distance sampling	1, 4, 5
Population		Basic <i>N</i> -mixture	1, 4, 5
How is the relative abundance of a species influenced by environmental variables?	3	Zero-inflated <i>N</i> -mixture	1, 4, 5, 6
How is abundance/density affected by environmental covariates?	4	Temporary emigration <i>N</i> -mixture	1, 4, 5, 6
What is the estimated abundance (or how many individuals)?	5	Beta-binomial <i>N</i> -mixture	1, 2, 4, 5
What is the probability of non-occupancy/temporary emigration?	6	Generalized <i>N</i> -mixture	1, 4, 5, 7
What are the population dynamics?	7	Spatially explicit density model	1, 4, 5
Community		Single visit <i>N</i> -mixture	1, 4, 5, 6
How species richness/diversity is affected by environmental covariates?	8	Multispecies <i>N</i> -mixture	1, 4, 5, 8, 9
What is the estimated richness/diversity (or how many species)?	9		

Table 3. Summary of published simulation studies for emerging methods of estimating abundance, with simulation settings, effects, and considerations for sample size. R is number of sites, T is number of visits, λ is the mean of the Poisson/NB distribution, p indicates detection probability, $1 - \phi$ is the probability of temporary emigration, ρ is correlation in detection of individuals, γ is arrival rate of new individuals, ω indicates survival probability, σ is the spatial correlation in counts, and ψ is the potential occupancy probability.

Method	Effects on abundance estimation	Sample size effects	Simulation settings	Reference
RN model	Bias of ~10–15% when $p = 0.1$;	Small at $R \leq 100$; Larger T and/or p counters small R	Wide (R, T) range, $\lambda = (4.61, 2.30, 1.61, 1.20, 0.92, 0.69, 0.51)$, $p = (0.1, 0.2)$, NB mean / variance ratios = (1.2, 2, 4)	Royle and Nichols (2003)
Basic N -mixture	Small positive bias when $R(p) = 20$ (0.25)	Adequate at $R = 20$	$R = (20, 50)$, $T = (3, 5, 10)$, $\lambda = (2, 5)$, $p = (0.25, 0.50)$	Royle (2004b)
Temporary emigration N -mixture	Unbiased in random emigration and spatially explicit emigration scenarios	Adequate at $R = 100$, lower values not investigated	$R = 100$, $T = 3$, $\lambda = 3.14$, $\phi = 0.5$, random emigration scenario vs. spatially explicit scenario (emigration dependent on home range size = [0, 10, 30])	Chandler et al. (2011)
Beta-binomial N -mixture	Better performance than the Basic N -mixture in the scenario with correlated detection (bias of 2% vs. 123%, respectively)	Adequate at $R = 200$, lower values not investigated	$R = 200$, $T = 3$, $\lambda = 4.6$, no correlation scenario with $p = 0.5$, correlation scenario $\rho = (0.15, 0.3)$ and $p = (0.7, 0.5)$, zero-inflated scenario with $\psi = 0.25$.	Martin et al. (2011)
Generalized N -mixture	Less biased than the Basic N -mixture in open population scenarios ($[\gamma, \omega] \neq [0, 1]$)	Adequate at $R = 20$; better results with $R = 100$	$(R, T) = (100, 10)$, $(R, T) = (20, 5)$, $\lambda = (2, 5)$, $p = (0.25, 0.50)$, $\gamma = (0, 1, 2)$, $\omega = (1, 0.8, 0.5)$	Dail and Madsen (2011)
Spatially explicit density model	Mean of estimates is biased (5-10%) when $\sigma = 0.5$, but mode is unbiased. With higher σ , estimates are unbiased. Bias is also reduced when effective encounter rate is increased.	15 x 15 sample point grid adequate, lower values not investigated	15 x 15 sample point grid, $\sigma = (0.5, 0.75, 1)$, effective encounter rate = (2.5, 5). Population size of (27, 45, 75)	Chandler and Royle (2013)

Single visit N -mixture	Overestimated with $R = 100$, converged to true values as R increased	Small at $R < 100$	$R = (100, 300, 500, 700, 1000)$, $\lambda = (2.13, 5.25)$, $p = (0.25, 0.65)$, $\psi = (0, 0.25)$ Sóllymos et al. (2012)
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Figure 1. Mechanisms that cause different types of zero observations in count surveys and how species rarity, detectability and sampling effort affect them. **(a)** False zeroes are due to either imperfect detection or temporary absence. True zeroes can occur when the sample unit is unoccupied by the species, due to demographic stochasticity, or due to ecological mechanisms such as unsuitable habitat or interspecific competition. **(b)** For common and detectable species (lower right), the majority of zeroes can be expected to result from ecological processes. As species detectability decreases, new false zeroes arise due to detection error (lower left). Species rarity results in fewer detections (dark green bars), additional true zeroes arise from unoccupied sample units (white bars) and increased demographic stochasticity (beige bars). **(c)** When the area sampled and/or the time of visit are small/short relative to the species home range or movements, individuals may not be available for detection during the survey, resulting in additional false zeroes and fewer non-zero observations.

Figure 2. Summary of the main modeling approaches for estimating abundance of unmarked animal populations described in the text. Boxes represent model features, diamonds represent additional parameters estimated by the models, and dotted and solid ellipses represent established and emerging methods, respectively. p indicates models that estimate detection probability, ψ indicates models that estimate potential occupancy probability, ϕ indicates models that estimate probability of temporary emigration from the sample unit, and ρ indicates models that account for correlation in detection of individuals. γ and ω are arrival rate and survival probability parameters, respectively, σ is the spatial correlation in counts, and Ω is the probability that a species is present in the supercommunity.

Capítulo 2

Raptor abundance in the Brazilian Cerrado and Pantanal: insights from single-visit detection-based methods for survey data

Abstract

Urbanization and the expansion of agricultural frontiers are among the main forces driving the degradation of natural habitats in Neotropical open habitats such as grasslands, savannas, steppes and wetlands. Inference and estimates of abundance are critical for quantifying the impacts of environmental change, yet imperfect detection can induce estimation error and obscure ecological patterns, and the sampling requirements of most detection-based estimation methods are often unmet in regional scale surveys of unmarked populations due to logistic and financial constraints. We employed a single visit N -mixture approach to model roadside raptor count data and investigate how land-use transformations in the Cerrado and Pantanal domains in Brazil have affected the populations of 12 species on a regional scale ($>300,000 \text{ km}^2$). We estimated the abundance of each species to assess the effects of seasonality and habitat availability and to generate projections across the entire study area while accounting for imperfect detection and zero-inflation. Detection of all species was influenced by time of day, with variable specific effects that follow expectations based on foraging and flying behavior. Amount of closed vegetation on roadsides and number of carcasses found during surveys also influenced detection of some species. Abundance of most species was negatively influenced by conversion of natural Cerrado and Pantanal habitats to anthropogenic uses, particularly pastures, soybean and sugar cane plantations, even for generalist species usually considered poor habitat-quality indicators. Protection of the remaining natural habitats is essential to prevent further decline of raptor populations in the study area, especially in the Cerrado domain.

Key-words: abundance estimation, count data, detection, raptor, hierarchical model, N -mixture model, population size, zero inflation, single visit, Cerrado, Pantanal

Resumo

A urbanização e a expansão das fronteiras agrícolas na região Neotropical estão entre as principais forças causadoras da degradação ambiental em habitats abertos naturais, como campos, savanas, estepes e áreas alagadas. Inferências e estimativas de abundância são críticas para a quantificação dos impactos de mudanças ambientais. Contudo, a detecção imperfeita pode induzir erros de estimativas e dificultar a identificação de padrões ecológicos, e os pré-requisitos de amostragem da maioria dos métodos de estimativa que levam em conta a detectabilidade frequentemente não são atingidos em amostragens de populações não-marcadas em escala regional devido a restrições logísticas e financeiras. Neste estudo aplicamos um método do tipo *N-mixture* baseado em visitas únicas para modelar dados de contagens de aves de rapina, obtidos durante amostragens de transecções com veículos em estradas, e investigar como transformações do uso do solo no Cerrado e Pantanal do Mato Grosso do Sul afetaram as populações de 12 espécies em uma escala regional ($>300.000 \text{ km}^2$). Levando em conta a detecção imperfeita e a inflação de zeros, estimamos a abundância de cada espécie para avaliar efeitos da sazonalidade e da disponibilidade de habitats, e para gerar projeções da abundância na área de estudo. A detecção de todas as espécies foi influenciada pelo horário de amostragem, com efeitos espécie-específicos congruentes com expectativas baseadas no comportamento de forrageamento e de voo. A quantidade de vegetação fechada às margens das estradas, e o número de carcaças encontradas também influenciou a detecção de algumas espécies. Tanto no Cerrado quanto no Pantanal, a abundância da maioria das espécies foi negativamente influenciada pela conversão de habitats naturais para habitats antrópicos, particularmente pastagens e plantações de soja e cana-de-açúcar, até mesmo para espécies generalistas que costumam ser consideradas como indicadores ruins da qualidade de habitats. A proteção dos habitats naturais remanescentes é essencial para prevenir um declínio ainda maior das populações de aves de rapina na área de estudo, especialmente no domínio do Cerrado.

Palavras-chave: estimativas de abundância, dados de contagens, detecção, aves de rapina, modelo hierárquico, modelo *N-mixture*, tamanho populacional, inflação de zeros, visita única, Cerrado, Pantanal

1 **Introduction**

2 Urbanization and the expansion of agricultural frontiers are among the main forces driving
3 the degradation of natural habitats in Neotropical biomes (Carrete *et al.* 2009). Avian
4 responses to changes in Neotropical open habitats such as grasslands, savannas, steppes and
5 wetlands, have become a major research interest in ecology and conservation biology,
6 following the fast and widespread conversion of many such areas to farming and ranching,
7 usually resulting in the impoverishment of local biodiversity (Cardoso & Bates 2002; Harris
8 *et al.* 2005). Monitoring of indicator species is a common approach to assess the health of
9 ecosystems (Margules & Pressey 2000). Raptors are good indicators of habitat change
10 because they are long-lived top predators or scavengers, occur across a wide spectrum of
11 habitat disturbances, and species are frequently associated with particular resources or habitat
12 types (Newton 1979; Sanchez-Zapata *et al.* 2003; Tella *et al.* 2008, but also Rodríguez-
13 estrella *et al.* 1998). Consequently, regional scale surveys that document changes in raptor
14 abundances over time or space are commonly used to draw inference on environmental
15 factors influence population size, and to determine species and areas of importance for
16 conservation management (Sanchez-Zapata *et al.* 2003; Sergio *et al.* 2008; Carrete *et al.*
17 2009).

18 Environmental change impacts both rare and common species. Studies investigating
19 these effects often model survey data to estimate species abundance and population trends to
20 understand how they are influenced by environmental factors. Yet sampling problems arise
21 from imperfect detection, a topic that has been widely discussed in the ecological literature
22 over the past decade (*e.g.* MacKenzie *et al.* 2002, Martin *et al.* 2005, Royle and Dorazio
23 2008, Iknayan *et al.* 2014). When unaccounted for, it can induce considerable error in
24 abundance estimation and mask important ecological patterns (Wenger & Freeman 2008). As
25 a result, several methods have been developed to deal with this issue, including distance

sampling, mark-recapture and N -mixture hierarchical models (Buckland *et al.* 2001; MacKenzie *et al.* 2002; Royle & Dorazio 2008). For unmarked populations (*i.e.*, no identification of individuals), information on the detection process is usually obtained by collecting ancillary data using distance sampling (Buckland *et al.* 2001) or by employing N -mixture models with temporally replicated surveys (Royle & Nichols 2003). In regional scale surveys, the sampling requirements for these approaches are often unmet because: (1) the spatial distribution of individuals relative to the point or line surveyed can be biased when surveys are performed along roads, rivers or paths (Buckland, Marsden & Green 2008); (2) distance measurements are difficult to obtain accurately for fast-moving individuals (*e.g.*, birds in flight; Buckland *et al.* 2008); and (3) visiting a site on several dates within a sampling season when the population is assumed to be closed increases travel costs and personnel time which, for a given budget, will reduce the number of sites that can be surveyed, narrowing the scale of the study (Lele, Moreno & Bayne 2012). Recently, Sólymos *et al.* (2012) proposed a single-visit N -mixture model that estimates abundance and detection probability from count data based and covariates that affect abundance and detection, provided the set of detection covariates differs from the abundance covariates by at least one numeric variable. The method, an extension of the single-visit occupancy model developed by Lele *et al.* (2012), allows detection-based analysis of count datasets where replicate surveys are unavailable.

In this paper we describe how land-use transformations in the Cerrado and Pantanal biomes in Brazil have affected the populations of 12 species of birds of prey. Because we were primarily interested in broad patterns over an area of 306,058 km², we relied on roadside counts and habitat data measured *ex situ* from recently developed high resolution GIS maps of the study area. We employed a single visit N -mixture approach (Sólymos *et al.* 2012) to investigate how the abundance of each species is influenced by seasonality and by

habitat availability and to generate projections of the species abundances across the entire study area while accounting for imperfect detection.

Methods

Study area

Fieldwork covered areas in the southern Cerrado and southern Pantanal biomes, in the Brazilian states of Mato Grosso do Sul and Goiás (Figure 1). The Cerrado has a seasonal climate with hot wet summers and warm dry winters, the dry period extending for 3 to 5 consecutive months between May and September (Cardoso & Bates 2002). Most of the Cerrado biome is covered by cerrado, a semideciduous to evergreen savanna vegetation that grows on the deep, well-drained and nutrient poor soils. This vegetation varies in physiognomy and composition, with five main structural types generally recognized (Cardoso & Bates 2002): (1) *cerradão*, a dense forest type (8–15 m tall) that often has a completely closed canopy, (2) *cerrado sensu stricto*, a woodland (5–8 m) with closed scrub and more scattered trees than in *cerradão*, (3) *campo cerrado*, an open scrubland (3–6 m) with few trees, (4) *campo sujo* grassland (2–3 m) with scattered shrubs, and (5) *campo limpo* grassland with few or no shrubs or taller woody plants. In addition, evergreen gallery forests (20–30 m) with dense and low understory often border the small rivers and streams of the region, and patches of semi-deciduous, deciduous and dry forests occur in areas of richer soil. The Cerrado, a biodiversity hotspot, has been reduced by pastures and agriculture to about 30% of its original area, and only 1.2-1.6% of this biome is currently protected (Myers et al. 2000, Machado et al., 2004, Silva et al. 2006). Agriculture in the region consists mainly of extensive annual cultures, such as soybean, maize and cotton, sugarcane plantations and eucalyptus afforestation.

1 The Pantanal is one of the largest continuous wetlands (Harris *et al.* 2005). Its climate
2 consists of hot, rainy summers (November-March) and warm, dry winters (April-October),
3 with occasional cold spells (Harris *et al.* 2005). A seasonal flooding pulse drives ecological
4 processes and patterns in the Pantanal, following an annual monomodal cycle with
5 amplitudes of 2-5 m and duration of 3 to 6 months (Harris *et al.* 2005). There is a delay of
6 about four months before the peak water level passes through the basin from north to south,
7 and the dry (low rainfall) season is already underway when water levels reach a peak in the
8 southern Pantanal. The system is also subject to annual variation in flooding intensity (Junk
9 *et al.* 2006). Influenced by the Amazon, Cerrado, Chaco and Atlantic Forest, vegetation in the
10 Pantanal is very heterogeneous, with different habitats, soil types, and inundation regimes
11 resulting in a variety of patchy landscapes. The predominant formations are grassland,
12 *cerradão*, *cerrado* sensu stricto, marshes, semideciduous forest, gallery forest, and floating
13 mats (Harris *et al.* 2005; Junk *et al.* 2006). Habitat loss in the Pantanal is increasing; more
14 than 40% of the forests and savanna habitats have already been altered for cattle ranching
15 through the introduction of exotic grass species (Harris *et al.* 2005). Although the Pantanal
16 wetland is Biosphere Reserve and considered a Wetland of International Importance, only
17 2.5% of the upper Paraguay River basin is formally protected (Harris *et al.* 2005).

18 19 *Field sampling*

20 We surveyed 12 species of diurnal birds of prey (Families *Accipitridae* and *Falconidae*,
21 Table 1) and New World vultures (Families *Cathartidae*, Table 1). Turkey (*Cathartes aura*)
22 and Lesser Yellow-Headed vultures (*C. burrovianus*) can be very difficult to distinguish in
23 the field depending on distance and light conditions, and we were unable to specifically
24 identify many of the detections. While we analyzed each species separately when assessing
25 covariate effects on abundance, to generate abundance predictions we grouped them as

1 “*Cathartes* vultures” to avoid removing a large number of undifferentiated observations from
2 the dataset.

3 We delimited nine survey transects covering approximately 1,740 linear km within
4 the Cerrado (~1400 km) and Pantanal (~ 340 km) biomes, maximizing coverage of the
5 habitat variation in the study area (Fig. 1). The routes included natural and anthropogenic
6 habitats, but were limited to roads that were drivable throughout the year. This was
7 challenging within the Pantanal region, where paved roads are scarce, and unpaved roads are
8 frequently flooded or in very bad conditions during the rainy season.

9 Roadside counts were conducted biannually during the dry (July/August) and wet
10 (January) seasons in 2011-2013 following protocols widely adopted for surveying birds of
11 prey (Fuller & Mosher 1981; Sanchez-Zapata *et al.* 2003; Carrete *et al.* 2009). In an effort to
12 include additional well-preserved areas of cerrado vegetation in the sample, we extended the
13 field efforts in 2012 to include ~140 km of road counts in Emas National Park (transect 9,
14 Fig. 1), which were surveyed in July 2012, Feb. 2013 and July 2013. Two observers (the
15 driver and another person) performed the counts, from 2 h after sunrise to 1–2 h before
16 sunset. Adverse weather conditions, such as heavy rain or fog, were avoided. Average driving
17 speed was 40–60 km/h. In a few cases it was necessary to stop the vehicle to identify the
18 birds, but we did not record new individuals observed during these stops. Each transect was
19 visited once per survey. In addition to the raptors, we counted carcasses sighted on or near
20 transects.

21 *GIS data processing*

23 We used a high-resolution vegetation cover and land use GIS map of the study area
24 developed by the Brazilian Agricultural Research Agency (EMBRAPA, Silva et al. 2011) to
25 extract explanatory habitat variables for models. This high detail map has 65 different
26 vegetation and land use categories, which we simplified in two steps into 10 habitat types

(Table 2). First, we removed areas in the south of the state that are within the domain of the Atlantic Forest, leaving only those within the Cerrado and Pantanal domains. We then summed the different sub-types of the most representative natural and anthropogenic formations (e.g., *cerradão*, *cerrado sensu stricto*, *campo cerrado*, *campo sujo* and *campo limpo* formations were all summed into one cerrado category). We also calculated the amount of closed vegetation in a 100 m buffer for use as a detection covariate (see below) by summing the area of habitat types that hinder visibility from the roadside when surveying (e.g., forest, *cerradão*, eucalyptus afforestations and sugar cane plantations). As a proxy for flooding of the Pantanal system in the study area, we obtained water surface elevation data at the time of surveys for the Paraguay and Miranda rivers, the major drainages in the region, from the Brazilian National Water Agency (ANA, 2013).

Survey transects were divided in 10 km segments over which we created a buffer of 2.5 km width on each side of the survey line. We then overlaid the buffer on the above-mentioned vector map of vegetation to obtain the areal proportions of each habitat type for each sample unit. Preliminary analysis showed that collinearity among habitats types was negligible, and habitat proportions did not change significantly with smaller or larger buffer widths (1km - 10 km). Thus, we used the 10 km transect segments with a buffer extending 2.5 km on each side (5 km total width) as sample units. To extract habitat data for the entire study area for abundance prediction analysis, we created a grid with cells of area equal to that of the sample units and calculated the proportion of each of the 10 habitat types in each grid cell in the study area. GIS analysis was done in ArcGIS v. 10.2 (ESRI 2013).

Abundance models, covariates, and model selection

We employed a conditional likelihood *N*-mixture approach for analyzing single visit survey count data in the presence of zero inflation and detection error (Sólymos *et al.* 2012) using

package ‘detect’ (Sólymos, Moreno & Lele 2013) in R, v. 3.0.0 (R Development Core Team 2014). Response variables were the counts of each species and the *Cathartes* vultures group in each sample unit (Appendix A). We fitted the models with zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) error distributions (both with a log-link) for the state process instead of their non-zero-inflated counterparts to account for the high number of zeroes in the counts. We used the ZIP error distribution for all species except the Turkey, Lesser Yellow-headed and Black vultures, the *Cathartes* vultures group, Snail Kites and Southern Caracaras (*Caracara plancus*). These species are often seen in aggregations, which can cause overdispersion in the count distribution. Instead, we used the ZINB distribution because it allows the mean to vary stochastically, thus accounting for the extra-Poisson variation.

The hierarchical structure of the conditional likelihood *N*-mixture model accepts use of explanatory variables (covariates) that may influence detection and abundance separately, and at least one continuous numeric variable in each level is required (Sólymos *et al.* 2012). Detection covariates used were time of day (hours after sunrise, linear and quadratic effects), area of closed vegetation in the vicinity of the transect line (100 m buffer), and the number of carcasses found in each sample unit for vultures and the southern caracara (Table 2). Abundance covariates were seasonality (factor with dry and wet season levels), river water surface elevation, and area proportion of the habitat types (Table 2). All continuous numerical covariates were scaled to unit variance and centered.

We determined the set of covariates that best predicts detection of each species by fitting models with every combination of the detection covariates and all of the abundance covariates, ranking them according to Akaike Information Criterion scores corrected for small samples and based on the conditional likelihood (AICc, Liang, Wu & Zou 2008; Donohue *et al.* 2011). We selected the detection covariate set from the model with the lowest

AICc value. To assess habitat and seasonal covariate effects, we fit models using the detection covariates previously determined and each of the abundance covariates (one abundance covariate per model), evaluating the effects using the β coefficients and AICc scores. We assessed goodness-of-fit with 90% confidence intervals based on 199 non-parametric bootstrap samples. This analysis was performed for all species and the *Cathartes* vultures group.

We sought the best combination of covariates to make abundance projections for each species across the study area. We defined a set of progressively simpler models via backwards-stepwise selection of the abundance covariates, starting with the full abundance term and the best detection term. In each step, we fit n models dropping one of the n abundance covariates from each, ranked them based on the AICc, and selected the model with the lowest AICc for the next step. We obtained the AICc weights of every model in the set, and excluded the models outside of a 0.95 cumulative weight. Then, we used the abundance term of each remaining model to predict the abundance in every grid cell of the study area. Non-habitat covariates in the abundance term, such as seasonality or river surface elevation, that were not in the grid dataset, were set to specific values (*e.g.*, dry season, maximum river surface elevation) for the predictions. We also calculated 95% prediction intervals using a Monte Carlo procedure, in which we drew 500 samples of the intercepts and β coefficients of each model from a Gaussian distribution with means and standard deviations equal to the bootstrap-based mean and std. deviation estimates of the input model. Finally, we averaged the predictions from each model using the recalculated AICc weights (Burnham & Anderson 2002).

Results

Habitat coverage and raptor counts

Pastures dominated anthropogenic land use in the study area (45%), whereas cerrado (25%) was the major natural habitat (Fig. 2). The relative proportion of habitat types in the sampled area did not differ significantly (Wilcoxon signed rank test $p = 0.49$) from that of the larger study area (Fig. 2), although anthropogenic habitats, especially annual agriculture, tended to have slightly higher proportions in the former than in the latter. This was expected, as anthropogenic habitats are concentrated alongside roads, whereas natural habitats remain away from roads. Eucalyptus and sugar cane plantations did not occur in the sampled area within the Pantanal, so were not included as covariates for species restricted to that area (see below).

We detected over 12,000 raptors during the six field surveys (Table 1, Appendix A). Black (*Coragyps atratus*) and Turkey vultures were by far the most common species detected, followed by the Southern Crested-Caracara (*Caracara plancus*). With the exception of the White-Tailed Hawk (*Geranoaetus albicaudatus*), the Aplomado Falcon (*Falco femoralis*) and the American Kestrel (*Falco sparverius*), abundance per sample unit was higher in the Pantanal than in the Cerrado (Table 1). As expected, the Snail Kite (*Rothramus sociabilis*), the Black-Collared Hawk (*Busarellus nigricolis*) and the Great Black Hawk (*Buteogallus urubitinga*), which occur mainly in wetland and riverine habitats (Ferguson-Lees & Christie 2001), were observed only in the Pantanal (Table 1). Due to lack of observations for these species in the Cerrado, we restricted the abundance modeling analysis to the Pantanal, even though they are not entirely absent from the Cerrado.

Factors affecting detection

Time of day was selected as a linear effect covariate on the detection of all species except Black Vulture, American Kestrel and Snail Kite, for which both linear and quadratic effects were selected (Appendix B). Five temporal patterns of detection can be distinguished from the weighted averages of the β coefficients (Figure 3, Table 3). The single linear negative effect in the Turkey and Lesser Yellow-Headed vultures, Southern Crested-Caracara, Savanna Hawk and Aplomado Falcon indicates that detection is higher in the morning and decreases later in the day. The general effect is similar in the Roadside and White-tailed hawks, but here the lower coefficient values result in a sharper change at the end of the day. The linear effect positively influenced detection of Great Black and Black-collared hawks, suggesting the opposite pattern for these species. The negative linear and positive quadratic effects associated with the Black Vulture and American Kestrel suggest that detection tends to be high at the start of the day, and diminishes and increases sharply in morning period, while Snail Kites show the opposite trend. Area of closed vegetation had a positive effect for Turkey Vulture ($\bar{\beta} = 0.588$) and American Kestrel ($\bar{\beta} = 0.162$) and a negative effect for Black Vulture ($\bar{\beta} = -1.796$) and Black-Collared Hawk ($\bar{\beta} = -0.082$). The number of carcasses observed during transects was an important covariate only for the Turkey Vulture, with a positive effect on detection ($\bar{\beta} = 1.796$).

Factors affecting abundance

For five of the 12 species the abundance covariate of the model that best explained variation in counts was the area proportion of an anthropogenic habitat type (Fig. 4, Table 3 and Appendix C), with a negative effect in all cases (pasture for Turkey, Lesser Yellow-headed and Black vultures, the *Cathartes* vultures group, Southern Crested-Caracara, and Aplomado Falcon; sugar cane for Roadside Hawk; Fig. 4). Conversely, the areal proportion of a natural

habitat type best explained counts in the Savanna Hawk (cerrado) and the Great Black Hawk (riverine vegetation), with a positive effect, and in the Black-collared Hawk (forest), with a negative effect. The season factor and river surface elevation were the most important covariates for, respectively, the American Kestrel (positive effect of wet season), and the Snail Kite (positive effect). The White-tailed Hawk was the only species for which a single covariate did not emerge as the best ($\Delta AICc > 2.0$).

Spatial projections of abundance

In the multiple abundance covariate model selection, considering all species and the covariates representing natural vegetation types, cerrado and riverine habitats were more often selected as important covariates than were forest and chaco (Appendix D). Among the anthropogenic land use covariates, agriculture and pasture were more frequent in the best-ranked models than secondary vegetation, eucalyptus, sugar cane and urban habitats (Appendix D). The season factor [wet vs. dry] was more often present in the best models than the covariate representing river surface elevation (Appendix D). With the exception of the Roadside Hawk, for which no seasonal covariate was present in the selected models (i.e., within 0.95 cumulative AICc weight), abundances were predicted in two scenarios: wet season with the minimum river surface elevation value recorded during the surveys, and dry season with the maximum river surface elevation (Table 4, Appendix F). Overall, the model λ estimates and the abundance predictions per grid cell have reasonable values. There are, however, over predicted cases, and these outliers result in biased estimate and prediction means (Table 4 and Appendix E). In these cases, the median is likely a better descriptor.

Discussion

Our single visit survey methodology allowed sampling at a regional scale to yield estimates of abundance as a function of environmental covariates for 12 raptor species while correcting for detection error, despite the lack of temporal replicates. As a result, we were able to assess how changes in habitat types, season, and river surface elevation affected raptor abundance (Table 3, Figure 4), and to generate abundance projections for the larger study area (Table 4, Appendix F). Below, we discuss methodological and biological facets of our study.

Methodological considerations

The high frequency of zeroes in our observed counts is indicative of several kinds of processes resulting in the lack of detections. The basic N -mixture abundance models distinguish zeroes due to imperfect detection (where the observed count is 0 but the underlying true abundance is greater than zero) from zeroes due to the state process (where both the observed count and the underlying abundance are equal to 0, Royle and Nichols 2003). Previous applications of zero-inflated N -mixture models include yet an additional type of zero to account for unoccupied sample units outside the species' distribution (Wenger & Freeman 2008; Joseph *et al.* 2009). Although the raptors studied here have very large geographic ranges and may occur throughout the study area (Ferguson-Lees & Christie 2001), their occurrence may be patchy at smaller scales so "non-occupancy" extra zeroes should occur. However, another kind of zero arises from temporary absences because raptors are highly mobile and have relatively large home ranges (Ferguson-Lees & Christie 2001). Thus, an individual may regularly use a site but be undetected at the time of survey because it is visiting a part of its home range outside of the sample unit. As a consequence of both mechanisms contributing to the zero-inflated count, it is not possible to decompose the zero-

inflation probability (ϕ) estimated by the models to each process (Appendices C and E). Thus, we avoid making ecological inferences regarding ϕ in our models, focusing instead on abundance and detection.

Use of ZINB N -mixture models for zero-inflated data has been criticized on the grounds that they often produce ecologically unrealistic parameter estimates, despite frequently being ranked as the “best model” compared to Poisson and ZIP N -mixture models (Kéry, Royle & Schmid 2005; Joseph *et al.* 2009). Joseph *et al.* (2009) suggested a ZINB N -mixture model can generate overly large estimates of site abundance ‘counteracted’ with excessively small detection probabilities. We justify use of the ZINB models, instead of ZIP models, for the Turkey, Lesser Yellow-headed and Black vultures (and the *Cathartes* vultures group), Snail Kites and Southern Caracaras because these species are often detected in large aggregations, which create an additional source of overdispersion. Thus, ZINB was employed to model this additional phenomenon, not as a means to provide a better model fit regardless of ecological realism. The estimates of abundance obtained with our ZINB models appear reasonable and more conservative than some estimates obtained with the ZIP models for species that do not aggregate (Appendices C and E). Our p values were not unrealistically low (Appendices C and E).

Our projections are a first attempt to generate regional maps of raptor abundance patterns in the Cerrado and Pantanal based on roadside surveys corrected for detection error (Appendix F). Numerous sources of bias intrinsic to the roadside survey method can influence raptor abundance, including an increased frequency of perch sites (e.g., power and telephone posts and lines, fences, road-signs, etc.), more food for scavenging species (i.e., road-kills), and increased edge habitats (Fuller & Mosher 1981; Millsap & Jr 1988; Meunier & Verheyden 2000; Carrete *et al.* 2009). In addition, the spatial distribution of our surveys transects was limited by road availability, resulting in large areas that were not sampled (e.g.,

the northwestern part of MS state). This may have influenced our projections of abundance by underrepresenting some habitat types, such as well-preserved forest, cerrado and chaco vegetation. Moreover, likelihood-based inference is not a small-sample procedure (Royle & Nichols 2003), so it is likely that the abundance predictions of species with fewer records (<200; Black-collared, Great Black and White-tailed hawks, Aplomado Falcon) are less reliable than those obtained for common species (Turkey, Lesser Yellow-headed and Black vultures, Savanna and Roadside hawks, Snail Kite and Southern Crested-Caracara). With these caveats, the maps presented in Appendix F should be viewed as depictions of the spatial and seasonal variation of abundance, rather than representations of the actual numbers of individuals occurring in the area.

Biological considerations

Although a systematic investigation of the potential factors that influence raptor detection is beyond the scope of this study, examination of the detection coefficients from the abundance models allows recognition of general patterns. Detection of raptors is often assumed to be linked with activity patterns, which in turn vary throughout the day as a result of changes in prey availability or flight requirements (Bunn et al. 1995). For example, species that prey on small mammals and birds are more active in the early morning than the late morning or afternoon because activity of their prey usually peaks around sunrise (Vieira & Baumgarten 1995; Halle 1995), while raptors that hunt reptiles have a delayed activity peak (Blair 2009). Vultures and other large raptors that require thermals and updrafts to soar face difficulty in flying in the early morning, and are more active later in the day (Fuller & Mosher 1981).

Our patterns of detection support these generalizations for raptors (Table 3, Appendix B). We found a negative effect of time of day on detection for Savanna, White-tailed and

Roadside hawks, Southern Crested-Caracara, and Aplomado Falcon, all of which feed on small mammals, reptiles or birds. The diet of the American Kestrel in the Cerrado is dominated by arthropods (>95% of prey species) that are distributed equally between diurnal and nocturnal species. This suggests the American Kestrel forages in crepuscular hours (Cabral et al. 2006), which might explain why its detection was lower during the early afternoon. A significant portion of the diets of Black-collared and Great Black Hawks consists of fish and other aquatic animals (e.g., amphibians, crabs). While the activity period of freshwater fishes is variable, many species are more active at higher water temperatures (Bizzotto *et al.* 2009), which might explain the positive effect of time of day on the detection of these two hawks in the Pantanal. In contrast, Snail Kite detection was highest during midday and early afternoon, when perching behavior peaks for this species (Beissinger 1983). Thus, behaviors that increase exposure and consequently detection are not necessarily linked to higher mobility. However, time of day did not affect the detection of Turkey, Lesser Yellow-headed and Black vultures as expected; the first two species were more likely to be seen earlier than later in the day, while detection of the later species was lowest in the middle of the day. A shift of activity peak to an earlier period could be a consequence of thermals available earlier in the day in tropical than in the temperate locations where detection patterns were previously studied (Bunn *et al.* 1995; Vergara 2010). On the other hand, observation of communal roosts, usually on well-exposed, high perches in the study area, could increase detection despite low activity.

Surprisingly, the amount of closed vegetation was an important detection covariate only a for Black Vulture and Black-collared Hawk, where it had a negative effect, and for Turkey Vulture and American Kestrel, where it had a positive effect (Table 3, Appendix B). Although visibility through closed habitat is undeniably lower (Fuller & Mosher 1981), perches on the borders – often associated with roads – are commonly used by raptors for

1 resting (including roosting), still-hunting and maintenance activities (preening, scratching,
2 basking/drying, etc.). This might increase detection in closed habitats (e.g., forests) compared
3 to other habitats, such as fields and pastures without such features. That detection of Turkey
4 Vultures was positively influenced by the amount of carcasses underlines the importance of
5 this resource, not only for feeding opportunities, but also as a potential ecological trap (Table
6 3, Appendix B). Vultures and other heavy raptors that land on roads are sometimes unable to
7 avoid fast incoming vehicles. Indeed, carcasses of 4 Black Vultures, 2 Turkey Vultures and 6
8 Southern Crested-Caracaras were found during the surveys, likely victims of highway
9 mortality. Such deaths are a frequent occurrence in the Cerrado and Pantanal (Fischer *et al.*
10 2003).

11 Despite the highly seasonal nature of the Cerrado and Pantanal, abundance of only the
12 American Kestrel and the Snail Kite were affected by seasonal flooding (Table 3, Figure 4).
13 The wet season in the Cerrado and Pantanal largely coincides with the breeding season of
14 American Kestrels in South America (October-March, Ferguson-Lees & Christie 2001), and
15 our wet season surveys were performed near the end of this period (late January-early
16 February). This, combined with a juvenile dependence period that can last more than a month
17 (Ferguson-Lees & Christie 2001) and a juvenile plumage that is not readily distinguishable
18 from the adult in the local race (*F. s. cinnamominus*), might explain the greater abundance in
19 the wet season, when reproduction occurs. Snail Kites, on the other hand, are well known to
20 perform dispersal and arrival movements in response to seasonal droughts, floods and snail
21 emergence (Bennetts & Kitchens 2000; Mooij *et al.* 2002; Darby *et al.* 2002), hence the
22 strong correlation between their abundance and higher flooding in the Pantanal.

23 The best two abundance predictors found for Savanna Hawk and Great Black Hawk,
24 cerrado and riverine habitats, confirm expectations about the habitat requirements of these
25 species (Table 3, Figure 4; Ferguson-Lees and Christie 2001, Carrete et al. 2009). The

1 abundance of the Black-collared Hawk was negatively related to forest habitat, which is
2 likely due to a strong association with ponds and rivers where it forages. Forests in the
3 Pantanal tend to occur only in higher elevation areas that are not subject to flooding (Table 3,
4 Figure 4; Junk *et al.* 2006).

5 Species-specific population responses of raptors to habitat transformation can be
6 variable and context-dependent (Sergio *et al.* 2008). Our results show that the abundance of
7 most species was negatively influenced by conversion of natural Cerrado and Pantanal
8 habitats to anthropogenic uses (Table 3, Figure 4), even for generalist species usually
9 considered poor habitat-quality indicators (e.g., Black and Turkey vultures, Southern
10 Crested-Caracara, Rodríguez-estrella *et al.* 1998; Zilio *et al.* 2013). In the state of MS, most
11 of the original Cerrado has been converted to pastures, soybean and sugarcane plantations,
12 and other anthropogenic habitats (Silva *et al.* 2011). In addition, conversion of natural
13 habitats to pastures and croplands in the Cerrado has led to severe erosion, causing sediment
14 deposition in the lowlands of the Pantanal and altering the patterns of water flow and
15 hydrological regimes (Harris *et al.* 2005).

16 Brazil's cattle herd is the largest in the world, and the country is by far the world's
17 leading exporter of beef (McAlpine *et al.* 2009). Yet half of the planted pastures in the
18 Cerrado are degraded and support few cattle because of reduced plant cover, invasion by
19 unpalatable plants, and termite mounds (Costa & Rehman 2005; Klink & Machado 2005).
20 The amount of pasture was strongly and negatively related to abundance for Turkey, Lesser
21 Yellow-headed and Black Vultures, Southern Crested Caracara and Aplomado Falcon,
22 Savanna Hawk and Snail Kite (Table 3, Figure 4). Cerrado passerines have mostly
23 experienced reduced abundances and strong community dissimilarity in pastures when
24 compared to natural grasslands (Tubelis & Cavalcanti 2000). Conversion of natural Cerrado
25 habitats to planted pastures may reduce local rainfall by up to 10%; and increase the length of

dry spells, and mean surface air temperature by 0.5° C (Hoffmann & Jackson 2000). Moreover, pastures in the Cerrado and Pantanal have very low herbaceous plant richness, often dominated by a single exotic species (e.g., *Brachiaria* sp.), in contrast with the high species richness found in natural grasslands (Filgueiras 1991; Junk *et al.* 2006). This effect, combined with similarly impoverished invertebrate and small vertebrate fauna, may contribute to reducing raptor abundance. Likewise, the thinning of the shrub and tree cover that occurs when forests or savanna habitats, such as cerrado *sensu strictu* and chaco, are converted to pastures probably causes the loss of resources for nesting, hunting and roosting, resulting in a lower carrying capacity.

Carvalho *et al.* (2009) showed that remnant natural vegetation area is similar between pasture and crop-dominated landscapes in the Cerrado. Soybeans and sugarcane have come to represent a powerful threat to the Cerrado as a result of the development of tolerant crop varieties, strong lobby and generous government subsidies, and rising demand for biofuels (e.g., biodiesel and ethanol) as an alternative energy source (Fearnside 2002; Carvalho *et al.* 2009). Soybean and sugarcane farms require heavy capital investment in machinery, land preparation and agricultural inputs. Soil fertility and topography are the most important features limiting this kind of mechanized agriculture. Consequently, wealthy agribusinesses, rather than poor farmers, are the main entrepreneurs. These plantations are often established in areas already cleared of natural vegetation, usually pastures owned by small farmers, who will then move to frontier areas and clear more natural habitats. Impact of this land use has increased because of the vast infrastructure development required for harvest and transportation (Fearnside 2002). Indeed, in a habitat selection study, Granzinolli (2009) found that raptors in the Cerrado of the neighboring state of São Paulo consistently rejected monocultures, especially sugar-cane. Underrepresentation of these land use types in our dataset, as well as eucalyptus afforestation, secondary vegetation and urban areas, is a

consequence of the small proportion of such habitats in the study area and the limited survey route options (Figure 2). It might have reduced their ranking as predictors of abundance for most raptor species and contributed to the wide confidence intervals observed (Table 3, Appendices C and D). Nevertheless, these anthropogenic habitats mostly had a negative effect on raptor abundance.

In summary, our results show that raptor populations have been significantly impacted by habitat degradation in the Cerrado and Pantanal of MS, even species considered as habitat generalists. These findings agree with patterns observed in other Neotropical biomes (Carrete *et al.* 2009). As such, protection of the remaining natural habitats is essential to prevent further decline of raptor populations in MS. Although none of the raptors investigated in this study are classified as endangered, we encountered another 21 species, including the rare King Vulture (*Sarcorhamphus papa*), the endangered Crowned Eagle (*Harpyhaliaetus coronatus*) and long distance migrants such as Osprey (*Pandion haliaetus*) and Peregrine Falcon (*Falco peregrinus*), that were recorded in numbers too small to allow inclusion in our analysis. They are likely to be subject to similar pressures in the study area.

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Table 1. Species and number of individuals detected during the road counts for each survey, and overall mean of individuals detected per survey sample unit (10 km road transect) in the Cerrado and Pantanal biomes.

Species	Feb/2011	Jul/2011	Feb/2012	Jul/2012 ^b	Feb/2013 ^b	Jul/2013 ^b	Total ^b	Detections/sample	
								Cerrado ^b	Pantanal
Family Cathartidae									
<i>Cathartes</i> vultures ^a	334	642	582	736	403	501	3198	2.02	5.40
Turkey Vulture (<i>C. aura</i>)	210	355	125	260	170	244	1364	0.90	2.26
Lesser-yellow-headed Vulture (<i>C. burrovianus</i>)	14	22	25	47	71	85	264	0.10	0.79
Unidentified (<i>Cathartes</i> spp.)	110	265	432	429	162	172	1570	1.02	2.36
Black Vulture (<i>Coragyps atratus</i>)	417	289	449	862	750	518	3285	1.31	9.63
Family Accipitridae									
Black-Collared Hawk (<i>Busarellus nigricolis</i>)	13	6	24	19	10	11	81	0	0.40
Great Black Hawk (<i>Buteogallus urubitinga</i>)	4	6	25	21	20	23	92	0	0.45
White-Tailed Hawk (<i>Geranoaetus albicaudatus</i>)	11	21	24	25	38	21	140	0.13	0.06
Savanna Hawk (<i>Buteogallus meridionalis</i>)	50	71	98	135	83	103	540	0.29	1.20
Snail Kite (<i>Rosthramus sociabilis</i>)	31	78	83	59	2	40	287	0	1.41
Roadside Hawk (<i>Rupornis magnirostris</i>)	34	32	54	67	33	54	274	0.16	0.57
Family Falconidae									
Southern Crested-Caracara (<i>Caracara plancus</i>)	147	220	224	217	331	262	1401	0.91	2.38
Aplomado Falcon (<i>Falco femoralis</i>)	4	8	7	26	39	13	97	0.09	0.03
American Kestrel (<i>Falco sparverius</i>)	37	28	58	32	52	41	248	0.23	0.09

^a Data used for modeling abundance of the *Cathartes* group

^b Includes transect in Emas National Park

Table 2. Explanatory variables used in the analysis. All covariates are continuous numeric variables, except season factor and road kills/carcasses.

Abundance			Detection	
Covariate	Group	Type	Covariate	Type
Cerrado savanna	Natural habitat	Area (proportion)	Time	Since sunrise
Forest	Natural habitat	Area (proportion)	Time ²	Since sunrise
Chaco dry savanna	Natural habitat	Area (proportion)	Closed vegetation	Area in 100m strip
Riverine vegetation	Natural habitat	Area (proportion)	Carcasses ^b	Count
Pasture	Anthropogenic habitat	Area (proportion)		
Annual agriculture	Anthropogenic habitat	Area (proportion)		
Secondary vegetation	Anthropogenic habitat	Area (proportion)		
Urban	Anthropogenic habitat	Area (proportion)		
Eucalyptus afforestation ^a	Anthropogenic habitat	Area (proportion)		
Sugar cane plantation ^a	Anthropogenic habitat	Area (proportion)		
River surface elevation	Seasonal	Height		
Season	Seasonal	Factor: wet x dry		

^a Not present in the Pantanal

^b Used only for Turkey, Lesser Yellow-headed and Black Vultures, and Southern Crested-Caracara models

Table 3. Model selection results for the single abundance covariate models, with β coefficients and their 90% non-parametric bootstrap confidence intervals (CI). Selection based on conditional likelihood AICc. “*Cathartes* vultures” group includes records of Turkey, Lesser Yellow-headed, and unidentified *Cathartes* vultures. Bold values are the AICc-weighted average of the detection β coefficients and CI.

Abundance			Detection						Model selection		
Turkey Vulture (<i>Cathartes aura</i>), binomial–zero-inflated negative binomial mixture (<i>n</i> = 1201 samples)											
Covariate	<i>β</i>	CI	<i>β</i> _{time}	CI _{time}	<i>β</i> _{closed habitat}	CI _{closed habitat}	<i>β</i> _{carcasses}	CI _{carcasses}	AICc	dAICc	Weight
Pasture	-0.168	(-0.29, -0.041)	-1.265	(-5.782, -0.382)	0.543	(-0.305, 2.619)	1.746	(0.109, 8.563)	1692.6	0.0	0.390
Urban	0.088	(-0.053, 0.186)	-0.941	(-5.919, -0.15)	0.493	(-0.44, 2.978)	1.837	(0.314, 9.007)	1695.3	2.6	0.104
Season (wet)	0.165	(-0.106, 0.503)	-1.09	(-5.896, -0.323)	0.511	(-0.069, 3.686)	3.083	(-0.075, 3.891)	1696.1	3.5	0.068
River level	0.112	(-0.063, 0.279)	-0.805	(-6.859, -0.123)	0.422	(-0.216, 2.991)	1.62	(0.215, 6.558)	1696.1	3.5	0.068
Agriculture	0.077	(-0.174, 0.268)	-0.876	(-5.616, -0.246)	0.462	(-0.159, 2.658)	1.898	(0.22, 6.043)	1696.5	3.8	0.058
Chaco	0.039	(-0.052, 0.112)	-1.057	(-7.633, -0.287)	0.524	(-0.306, 2.667)	1.683	(0.304, 7.998)	1696.7	4.0	0.052
Cerrado	-0.041	(-0.171, 0.071)	-1.178	(-6.567, -0.258)	0.647	(-0.249, 3.777)	1.79	(-1.009, 7.229)	1696.9	4.3	0.046
Cane	0.037	(-0.217, 0.127)	-2.481	(-20.336, -0.47)	1.326	(-0.293, 3.868)	1.231	(-0.868, 13.782)	1697.0	4.3	0.045
Eucalyptus	-0.037	(-0.184, 0.156)	-1.955	(-9.659, -0.301)	1.057	(-0.391, 7.277)	1.414	(-0.573, 10.568)	1697.0	4.4	0.044
Riverine	-0.018	(-0.125, 0.077)	-1.209	(-6.414, -0.269)	0.659	(-0.282, 3.055)	1.77	(-0.488, 8.28)	1697.0	4.4	0.043
Sec. vegetation	0.001	(-0.115, 0.064)	-0.951	(-6.654, -0.236)	0.426	(-0.294, 3.425)	1.599	(0.064, 6.226)	1697.1	4.5	0.042
Forest	-0.001	(-0.296, 0.104)	-1.267	(-7.392, -0.19)	0.627	(-0.182, 4.277)	1.593	(-0.678, 4.786)	1697.1	4.5	0.041
		Weighted average	-1.220	(-6.950, -0.299)	0.588	(-0.283, 3.194)	1.796	(-0.044, 7.977)			

Lesser Yellow-headed Vulture (*Cathartes burrovianus*), binomial–zero-inflated negative binomial mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI _{time}	AICc	dAICc	Weight
Pasture	-0.411	(-0.633, -0.208)	-0.394	(-1.072, -0.056)	342.5	0.0	0.851
Eucalyptus	-0.716	(-6.588, -0.305)	-0.318	(-0.721, 0.104)	348.7	6.2	0.039
Chaco	0.132	(-0.044, 0.243)	-0.296	(-0.93, 0.022)	349.8	7.2	0.023
Cerrado	0.15	(-0.017, 0.259)	-0.401	(-0.751, -0.107)	349.9	7.3	0.022
Season (wet)	-0.389	(-0.804, 0.009)	-0.217	(-0.975, 0.388)	350.9	8.3	0.013
Agriculture	-0.197	(-0.586, 0.128)	-0.339	(-1.036, -0.021)	351.6	9.1	0.009
Forest	0.13	(-0.201, 0.322)	-0.332	(-1.065, 0.012)	351.7	9.1	0.009
Sec. vegetation	0.053	(-0.26, 0.144)	-0.337	(-0.871, 0.008)	351.9	9.4	0.008
Riverine	-0.039	(-0.215, 0.099)	-0.338	(-0.764, -0.006)	352.1	9.6	0.007
River level	0.068	(-0.37, 0.507)	-0.321	(-0.864, -0.04)	352.2	9.7	0.007
Urban	-0.019	(-0.438, 0.156)	-0.342	(-0.855, -0.012)	352.3	9.7	0.007
Cane	0.01	(-12.727, 0.071)	-0.342	(-0.874, 0.009)	352.3	9.7	0.007
Weighted average			-0.384	(-1.039, -0.041)			

***Cathartes* vultures (*C. aura* and *C. burrovianus*), binomial–zero-inflated negative binomial mixture ($n = 1201$ samples)**

Covariate	β	CI	β_{time}	CI _{time}	$\beta_{\text{closed habitat}}$	CI _{closed habitat}	AICc	dAICc	Weight
Pasture	-0.278	(-0.359, -0.202)	-1.353	(-2.159, -0.797)	0.664	(-0.104, 1.582)	3422.2	0.0	0.999

Chaco	0.154	(0.109, 0.199)	-1.116	(-3.783, -0.347)	0.718	(0.038, 1.911)	3438.8	16.6	<0.000
Eucalyptus	-0.190	(-0.287, -0.106)	-1.240	(-3.872, -0.389)	0.776	(0.034, 1.937)	3442.3	20.1	<0.000
River level	-0.241	(-0.396, -0.115)	-1.273	(-3.378, -0.428)	0.614	(0.048, 1.685)	3444.9	22.7	<0.000
Riverine	-0.048	(-0.122, 0.019)	-1.260	(-4.989, -0.409)	0.844	(0.036, 2.379)	3451.1	28.9	<0.000
Forest	0.045	(-0.028, 0.141)	-1.386	(-8.833, -0.440)	0.819	(-0.193, 2.697)	3451.5	29.3	<0.000
Cerrado	0.031	(-0.041, 0.092)	-1.319	(-5.353, -0.335)	0.759	(0.023, 3.033)	3451.8	29.6	<0.000
Cane	0.034	(-0.118, 0.099)	-1.368	(-6.017, -0.474)	0.828	(0.023, 3.033)	3451.9	29.7	<0.000
Sec. vegetation	0.020	(-0.038, 0.067)	-1.277	(-3.927, -0.197)	0.779	(0.044, 1.885)	3451.9	29.7	<0.000
Urban	-0.020	(-0.112, 0.045)	-1.312	(-4.587, -0.320)	0.785	(-0.38, 1.899)	3452.0	29.8	<0.000
Season (wet)	0.036	(-0.136, 0.241)	-1.246	(-4.923, -0.275)	0.734	(0.074, 2.012)	3452.1	29.9	<0.000
Agriculture	0.014	(-0.131, 0.110)	-1.317	(-4.732, -0.303)	0.806	(0.081, 2.064)	3452.1	30.0	<0.000
Weighted average			-1.353	(-2.160, -0.797)	0.664	(-0.105, 1.583)			

Black Vulture (*Coragyps atratus*), binomial–zero-inflated negative binomial mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI _{time}	β_{time}^2	CI _{time} ²	$\beta_{\text{closed habitat}}$	CI _{closed habitat}	AICc	dAICc	Weight
Pasture	-0.713	(-0.925, -0.491)	-19.758	(-67.214, -4.954)	17.357	(4.599, 54.748)	-0.924	(-4.427, 5.232)	2317.3	0.0	0.998
Riverine	-0.382	(-0.539, -0.118)	-2.029	(-24.482, 10.581)	2.328	(-7.642, 31.852)	1.189	(-4.242, 4.479)	2330.1	12.8	0.002
Cerrado	0.289	(0.105, 0.445)	-1.988	(-46.802, 4.350)	2.388	(-3.037, 43.818)	0.213	(-4.016, 13.832)	2334.3	17.0	<0.000
Cane	-1.243	(-1.243, -1.243)	-1.856	(-1.856, -1.856)	2.388	(2.388, 2.388)	0.651	(0.651, 0.651)	2338.3	21.0	<0.000

Sec. vegetation	0.159	(0.159, 0.159)	-2.044	(-2.044, -2.044)	2.627	(2.627, 2.627)	0.945	(0.945, 0.945)	2341.5	24.2	<0.000
River level	-0.290	(-0.290, -0.290)	-1.577	(-1.577, -1.577)	2.128	(2.128, 2.128)	0.436	(0.436, 0.436)	2342.8	25.5	<0.000
Eucalyptus	-0.243	(-0.243, -0.243)	-1.772	(-1.772, -1.772)	2.373	(2.373, 2.373)	0.458	(0.458, 0.458)	2345.1	27.7	<0.000
Forest	0.111	(0.111, 0.111)	-1.635	(-1.635, -1.635)	2.212	(2.212, 2.212)	0.452	(0.452, 0.452)	2345.3	27.9	<0.000
Season (wet)	0.251	(-0.160, 0.909)	-2.165	(-17.397, -0.420)	2.633	(0.590, 16,654)	0.553	(-0.580,3,223)	2345.9	28.6	<0.000
Chaco	0.004	(0.004, 0.004)	-1.680	(-1.680, -1.680)	2.242	(2.242, 2.242)	0.543	(0.543, 0.543)	2346.6	29.3	<0.000
Agriculture	-0.053	(-0.394, -0.022)	-1,659	(-3,625, -1,339)	2.117	(1.799, 4.503)	0.585	(0.101, 0.585)	2346.8	29.5	<0.000
Urban	-0.057	(-0.274, 0.134)	-2.241	(-37.338, 0.462)	2.839	(0.027, 34.792)	0.587	(-0.708, 7.261)	2346.9	29.6	<0.000
Weighted average			-19.726	(-67.141, -4.928)	17.330	(4.579, 54.709)	-0.921	(-4.427, 5.233)			

Southern Crested-Caracara (*Caracara plancus*), binomial–zero-inflated negative binomial mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI_{time}	AICc	dAICc	Weight
Pasture	-0.445	(-0.576, -0.318)	-0.430	(-1.196, 2.152)	1468.1	0.0	1.000
Chaco	0.248	(0.079, 0.250)	3,982	(-0.837,15.112)	1485.4	17.2	<0.000
Eucalyptus	-0.479	(-0.830, -0.185)	2.844	(-2.030, 7.817)	1489.0	20.8	<0.000
Forest	0.214	(-0.025, 0.544)	5.701	(-7.480, 32.611)	1490.0	21.9	<0.000
Cane	-0.101	(-0.242, 0.022)	11.719	(-5.389, 41.130)	1493.7	25.6	<0.000
Riverine	-0.075	(-0.200, 0.031)	7.463	(-2.554, 12.212)	1494.1	26.0	<0.000
River level	0.061	(-0.242, 0.309)	6.402	(-6.496, 32.838)	1495.3	27.2	<0.000

Cerrado	0.001	(-0.129, 0.104)	6.040	(-6.947, 18.919)	1495.7	27.6	<0.000
Urban	-0.069	(-0.283, 0.113)	4.369	(-1,623, 16.406)	1495.9	27.7	<0.000
Season (wet)	0.158	(-0.155, 0.413)	-0.350	(-1.450, 4.461)	1495.9	27.8	<0.000
Agriculture	0.066	(-0.084, 0.161)	-0.295	(-2.672, 6.855)	1496.0	27.9	<0.000
Sec. vegetation	0.006	(-0.152, 0.097)	-0.369	(-7,176, 24.083)	1496.5	28.4	<0.000
Weighted average			-0.430	(-1.197, 2.156)			

Savanna Hawk (*Buteogallus meridionalis*), binomial–zero-inflated Poisson mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI_{time}	AICc	dAICc	Weight
Cerrado	0.231	(0.095, 0.311)	-0.132	(-1.537, 0.147)	805.4	0.0	0.910
Pasture	-0.307	(-0.440, -0.165)	-0.159	(-1.720, 0.067)	810.0	4.6	0.089
Agriculture	-0.856	(-1.461, -0.500)	-0.071	(-0.933, 0.164)	819.4	14.0	<0.000
Cane	-5.243	(-5.273, -5.014)	-1.659	(-9.828, 3.565)	820.6	15.2	<0.000
Chaco	0.133	(0.072, 0.198)	-0.111	(-1.601, 0.118)	826.1	20.7	<0.000
Season (wet)	-0.420	(-0.684, -0.057)	-52.162	(-215.571, -29.638)	827.8	22.4	<0.000
River level	-0.371	(-0.681, -0.011)	-0.121	(-1.485, 0.918)	831.7	26.3	<0.000
Eucalyptus	-0.207	(-0.442, -0.094)	-0.080	(-1.410, 0.138)	834.3	29.0	<0.000
Forest	-0.046	(-0.203, 0.082)	-0.079	(-1.125, 0.154)	839.1	33.7	<0.000
Sec. vegetation	-0.023	(-0.101, 0.042)	-76,688	(-79.261, -70.912)	839.3	34.0	<0.000

Urban	0.045	(-0.454, 0.301)	-47.329	(-51.306, -33.025)	839.3	34.0	<0.000
Riverine	0.018	(-0.207, 0.167)	-0.079	(-1.326, 0.234)	839.6	34.3	<0.000
Weighted average			-0.136	(-1.560, 0.142)			

Roadside Hawk (*Rupornis magnirostris*), binomial–zero-inflated Poisson mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI_{time}	AICc	dAICc	Weight
Cane	-5.120	(-5.192, -4.431)	-6.748	(-66.053, -5.007)	294.4	0.0	0.391
Forest	0.091	(0.026, 0.161)	-0.751	(-40.286, 2.373)	297.2	2.9	0.094
Riverine	-0.160	(-0.465, 0.069)	-0.602	(-19.270, 1.756)	297.5	3.1	0.082
Cerrado	-0.082	(-0.408, 0.117)	-0.637	(-83.298, 13.552)	298.0	3.7	0.063
Sec. vegetation	-0.112	(-0.437, 0.031)	-0.660	(-128.528, 6.375)	298.1	3.7	0.060
Pasture	-0.132	(-0.317, 0.029)	-0.622	(-36.330, 5.927)	298.4	4.0	0.052
Chaco	0.084	(-0.084, 0.220)	-0.610	(-40.429, 2.382)	298.6	4.2	0.048
Eucalyptus	-0.096	(-0.607, 0.078)	-0.620	(-79.392, 5.412)	298.6	4.2	0.047
Urban	-0.041	(-0.487, 0.162)	-0.593	(-43.461, 2.702)	298.7	4.4	0.044
River level	-0.190	(-0.566, 0.223)	-0.622	(-36.050, 5.755)	298.8	4.4	0.044
Season (wet)	0.021	(-0.450, 0.481)	-0.588	(-26.739, 3.927)	299.0	4.6	0.039
Agriculture	-0.148	(-0.950, 0.139)	-0.555	(-19.235, 4.576)	299.1	4.7	0.037
Weighted average			-17.414	(-107.335, -13.442)

White-tailed Hawk (*Geranoaetus albicaudatus*), binomial–zero-inflated Poisson mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI_{time}	AICc	dAICc	Weight
Riverine	-0.255	(-0.803, 0.110)	-1013.296	(-1013.25, -1005.047)	169.2	0.0	0.149
Urban	-12.409	(-26.018, -11.478)	-0.188	(-0.658, 0.245)	169.3	0.1	0.141
Cane	-13.671	(-35.832, -12.593)	-0.198	(-0.863, 0.273)	170.0	0.8	0.098
River level	-0.652	(-1.296, 0.381)	-0.212	(-0.976, 0.558)	170.2	1.0	0.089
Chaco	0.434	(-3.037, 0.943)	-0.220	(-4.534, 0.333)	170.4	1.2	0.081
Season (wet)	-0.359	(-1.064, 0.468)	-0.102	(-0.907, 0.961)	170.4	1.2	0.083
Forest	0.001	(-1.998, 0.623)	-78.638	(-5624.612, -55.225)	170.9	1.7	0.063
Sec. vegetation	-0.091	(-7.919, 0.175)	-0.198	(-1.002, -0.339)	170.9	1.7	0.062
Agriculture	0.087	(-0.495, 0.342)	-0.226	(-52.101, 0.422)	171.0	1.8	0.061
Pasture	-0.091	(-0.420, 0.175)	-0.225	(-0.986, 0.681)	171.0	1.8	0.061
Eucalyptus	-0.107	(-6.347, 0.195)	-0.190	(-1.036, 0.420)	171.1	1.9	0.058
Cerrado	0.009	(-0.359, -0.199)	-0.190	(-1.036, 0.599)	171.3	2.1	0.052
Weighted average			-156.173	(-511.875, -152.944)			

American Kestrel (*Falco sparverius*), binomial–zero-inflated Poisson mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI_{time}	β_{time}^2	$\text{CI}_{\text{time}}^2$	$\beta_{\text{closed habitat}}$	$\text{CI}_{\text{closed habitat}}$	AICc	dAICc	Weight
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Season (wet)	0.739	(0.295, 1.189)	-5.830	(-190.592, 1.050)	4.408	(-3131, 126.646)	0.177	(-4.025, 0.580)	312.2	0.0	0.736
Eucalyptus	0.182	(0.073, 0.261)	-21.709	(-3365.406, 1.708)	14.857	(-10.109, 2458.349)	0.065	(-2.601, 1.830)	315.8	3.6	0.124
Urban	-0.404	(-0.789, -0.197)	-9.379	(-1699.579, 1.659)	6.877	(-16.787, 1112.848)	0.167	(-13.414, 22.667)	316.7	4.5	0.078
Agriculture	-0.188	(-0.595, 0.034)	-8.845	(-1405.001, 0.941)	6.486	(-18.792, 902.142)	0.155	(-45.226, 1.051)	320.8	8.6	0.010
Pasture	0.136	(-0.050, 0.359)	-8.465	(-1334.898, 2.886)	6.212	(-16.357, 867.512)	0.196	(-14.675, 3.870)	321.1	8.9	0.009
Riverine	-0.113	(-0.361, 0.135)	-8.639	(-1200.258, -2.035)	6.339	(-1.357, 935.580)	0.167	(-8.525, 3.750)	321.2	9.0	0.008
River level	-0.309	(-1.094, 0.426)	-8.971	(-4089.718, -0.059)	6.578	(-4.034, 3711.853)	0.159	(-96.387, 2.562)	321.6	9.4	0.007
Cane	0.095	(-41.443, 0.363)	-8.491	(-1851.412, 4.542)	6.237	(-21.101, 1390.122)	0.037	(-12.772, 3.297)	321.7	9.5	0.007
Cerrado	-0.072	(-0.365, 0.093)	-9.040	(-2437.306, 0.093)	6.599	(0.279, 1744.690)	0.155	(-34.906, 6.478)	321.8	9.6	0.006
Chaco	0.099	(-0.308, 0.401)	-9.512	(-4049.966, 0.740)	6.940	(-9.708, 2926.724)	0.157	(-17.838, 8.696)	321.9	9.7	0.006
Forest	0.052	(-0.677, 0.361)	-9.190	(-4039.481, 1.422)	6.709	(-5.822, 3097.267)	0.152	(-26.525, 45.982)	322.1	9.9	0.005
Sec. vegetation	0.019	(-0.391, 0.174)	-8.934	(-1591.931, 2.315)	6.535	(-19.851, 1261.691)	0.156	(-29.893, 1.893)	322.1	9.9	0.005
Weighted average			-8.259	(-831.282, 1.168)	6.022	(-5.675, 592.349)	0.162	(-9.213, 2.875)			

Apomado Falcon (*Falco femoralis*), binomial–zero-inflated Poisson mixture ($n = 1201$ samples)

Covariate	β	CI	β_{time}	CI _{time}	AICc	dAICc	Weight
Pasture	-0.838	(-2.486, -0.498)	-0.903	(-3.338, -0.551)	115.5	0.0	0.540
Riverine	-1.847	(-3.510, -1.014)	-0.741	(-2.918, -0.526)	116.5	1.0	0.330
Cerrado	0.344	(0.169, 0.578)	-0.705	(-3.276, -0.400)	118.4	2.8	0.130

Chaco	-9.925	(-106.839, -8.091)	-0.525	(-2.441, -0.135)	128.8	13.2	<0.000
Forest	-9.337	(-20.939, -7.809)	-0.660	(-3.343, -0.090)	129.1	13.6	<0.000
Urban	-11.444	(-14.322, -9.449)	-0.680	(-6.771, -0.237)	131.1	15.5	<0.000
Sec. vegetation	-0.452	(-6.428, 0.174)	-0.768	(-3.407, -0.310)	131.5	16.0	<0.000
Cane	-5.069	(-10.649, -3.469)	-0.629	(-3.314, -0.127)	131.6	16.1	<0.000
Eucalyptus	-185.800	(-194.793, -181.525)	-0.807	(-25.507, -0.443)	132.2	16.6	<0.000
River level	-0.317	(-1.573, 28.927)	-0.917	(-3.117, -0.307)	132.7	17.2	<0.000
Agriculture	-0.001	(-0.292, 0.176)	-0.802	(-5.140, -0.374)	132.9	17.4	<0.000
Season	-0.057	(-0.600, 0.832)	-0.731	(-20.657, -0.251)	132.9	17.4	<0.000
Weighted average			-0.824	(-3.197, 0.523)			

Snail Kite (*Rosthramus sociabilis*, binomial–zero-inflated negative binomial mixture ($n = 195$ samples))

Covariate	β	CI	β_{time}	CI_{time}	β_{time}^2	$\text{CI}_{\text{time}}^2$	AICc	dAICc	Weight
River level	1.132	(0.733, 1.682)	7.496	(-1.292, 120.559)	-10.064	(-188.617, -2.580)	166.1	0.0	0.982
Agriculture	-3.043	(-18.135, -1.063)	4.017	(-140.361, 49.228)	-13.105	(-82.647, 71.019)	175.6	9.6	0.008
Riverine	-0.487	(-0.966, -0.133)	16.028	(-92.031, 63.489)	-22.578	(-118.078, 41.209)	177.4	11.3	0.003
Pasture	-0.897	(-1.816, -0.235)	6.697	(-34.523, 52.306)	1.431	(-45.218, 37.891)	178.8	12.7	0.002
Urban	-0.164	(-0.164, -0.164)	15.450	(15.450, 15.450)	-21.307	(-21.307, -21.307)	179.5	13.4	0.001
Cerrado	-0.607	(-5.981, 0.065)	-2.207	(-169.435, 17.513)	-7.476	(-58.381, 84.018)	179.9	13.8	0.001

Sec. vegetation	-0.355	(-5.761, 0.066)	-11.810	(-70.099, 5.330)	-0.365	(-42.128, 22.815)	180.0	13.9	<0.000
Chaco	-0.231	(-0.137, 0.765)	-12.659	(-232.647, 36.953)	1.397	(-86.912, 99.758)	180.2	14.1	<0.000
Season	-0.399	(-1.618, 0.764)	-10.635	(-256.178, 49.404)	-0.315	(-171.331, 134.668)	180.8	14.7	<0.000
Forest	0.415	(-0.966, 2.850)	-7.020	(-203.800, 37.838)	-3.442	(-79.179, 109.690)	181.0	14.9	<0.000
Weighted average			7.440	(-3.493, 119.161)	-10.095	(-186.632, -1.428)			

Black-collared Hawk (*Busarellus nigricolis*), binomial–zero-inflated Poisson mixture ($n = 195$ samples)

Covariate	β	CI	β_{time}	CI _{time}	$\beta_{\text{closed habitat}}$	CI _{closed habitat}	AICc	dAICc	Weight
Forest	-1.504	(-3.376, -0.651)	385.880	(352.397, 405.643)	52.483	(43.949, 75.583)	114.0	0.0	0.562
Cerrado	0.232	(0.044, 0.469)	-270.769	(-273.362, -267.815)	-148.569	(-151.605, -144.694)	116.4	2.5	0.165
River level	-0.381	(-0.929, -0.011)	-8.337	(-165.896, -4.389)	-6.135	(-142.038, 3.676)	118.3	4.3	0.065
Pasture	-0.498	(-2.663, 0.006)	-27.099	(-59.419, -22.308)	-23.230	(-50.987, -14.160)	118.3	4.4	0.063
Riverine	0.245	(-0.164, 0.702)	-6.827	(-110.967, -4.167)	-6.529	(-123.936, -0.093)	119.4	5.4	0.038
Chaco	-0.224	(-0.464, 0.049)	-75.312	(-84.171, -57.734)	-77.904	(-78.477, -64.881)	119.6	5.6	0.034
Season	0.716	(0.026, 1.544)	-1.097	(-191.802, -0.143)	0.199	(-195.212, 1.736)	119.7	5.8	0.031
Sec. vegetation	-13.825	(-2084.972, -9.788)	-12.480	(-4433.981, -9.478)	-10.947	(-2868.862, 0.426)	120.2	6.2	0.025
Agriculture	-0.067	(-24.834, 0.643)	-7.678	(-166.917, -3.671)	-6.381	(-129.059, 0.778)	122.3	8.3	0.009
Urban	3.062	(-204.478, 133.732)	-7.821	(-589.116, -2.052)	-6.347	(-227.327, 9.732)	122.3	8.3	0.009
Weighted average			166.800	(8.533, 179.843)	-0.082	(-100.677, 15.969)			

Great Black Hawk (*Buteogallus urubitinga*), binomial–zero-inflated Poisson mixture ($n = 195$ samples)

Covariate	β	CI	β_{time}	CI _{time}	AICc	dAICc	Weight
Riverine	0.402	(0.173, 0.607)	1.891	(1.111, 73.184)	111.3	0.0	0.335
Sec. vegetation	0.717	(0.158, 1.036)	1.834	(0.761, 6.222)	111.9	0.6	0.253
Agriculture	-9.843	(-22.305, -7.491)	1.662	(0.273, 40.825)	112.8	1.5	0.157
Cerrado	0.206	(0.040, 0.397)	1.517	(0.104, 552.805)	114.6	3.3	0.065
Season	-0.420	(-0.869, 0.040)	1.501	(0.508, 236.214)	115.7	4.4	0.038
Forest	-0.478	(-1.384, 0.026)	1.234	(0.204, 40.570)	115.8	4.5	0.036
Urban	-5.769	(-9.347, -3.824)	1.347	(0.591, 9.728)	115.8	4.5	0.035
Chaco	-0.164	(-0.429, 0.075)	1.462	(0.304, 94.951)	116.0	4.7	0.033
River level	0.235	(-0.146, 0.539)	1.586	(0.336, 49.663)	116.1	4.8	0.030
Pasture	0.002	(-1.949, 0.368)	1.406	(0.264, 38.826)	117.1	5.8	0.019
Weighted average			1.727	(0.687, 84.698)			

Table 4. Summary of the abundance predictions over the study area, generated with the AICc-weighted average of the multiple abundance covariate models for each species, with 95% prediction interval bounds (PI). Scenario is the setting of the seasonal covariates used for predictions: wet season with minimum river surface elevation (wet-min.) and dry season with maximum river surface elevation (dry-max.), except for the Roadside Hawk where no seasonal covariate was present in the models selected for this species (Appendix C). Predictions are per grid cell (area = 50 km²).

Species	Scenario	Predicted abundance					
		Mean	PI	Median	PI	Std. Dev.	PI
<i>Cathartes</i> vultures	Wet-min.	4.862	(3.249, 7.669)	4.079	(2.863, 6.012)	2.003	(1.274, 6.770)
	Dry-max.	3.449	(2.282, 5.477)	2.893	(2.013, 4.286)	1.423	(0.880, 4.984)
Black Vulture	Wet-min.	39.069	(1.224, >1000)	2.796	(0.723, 88.753)	972.073	(2.187, >1000)
	Dry-max.	25.709	(0.861, >1000)	1.819	(0.507, 60.051)	641.331	(1.567, >1000)
Southern Crested-Caracara	Wet-min.	0.909	(0.086, 916.050)	0.693	(0.066, 760.439)	0.553	(0.060, 398.874)
	Dry-max.	0.975	(0.098, 635.049)	0.742	(0.075, 514.75)	0.602	(0.071, 306.728)
Savanna Hawk	Wet-min.	4.978	(1.437, >1000)	3.075	(1.226, 8.022)	22.490	(0.682, >1000)
	Dry-max.	3.842	(1.224, >1000)	2.379	(1.036, 5.889)	17.177	(0.592, >1000)
Roadside Hawk	Single scenario	0.603	(0.144, >1000)	0.617	(0.151, >1000)	0.135	(0.035, >1000)
American Kestrel	Wet-min.	2.202	(0.502, >1000)	2.080	(0.520, 20.088)	1.902	(0.118, >1000)
	Dry-max.	0.972	(0.258, >1000)	0.918	(0.266, 6.635)	0.855	(0.055, >1000)
Aplomado Falcon	Wet-min.	>1000	(>1000, >1000)	3.313	(0.034, >1000)	>1000	(>1000, >1000)
	Dry-max.	>1000	(>1000, >1000)	3.295	(0.032, >1000)	>1000	(>1000, >1000)
White-tailed Hawk	Wet-min.	5.862	(0.134, >1000)	6.115	(0.135, >1000)	0.812	(0.002, >1000)
	Dry-max.	4.216	(0.206, >1000)	4.336	(0.206, >1000)	0.511	(0.001, >1000)
Snail Kite ^a	Wet-min.	>1000	(6.052, >1000)	0.542	(0.024, >1000)	>1000	(232.224, >1000)
	Dry-max.	>1000	(2.527, >1000)	2.590	(0.137, >1000)	>1000	(67.555, >1000)
Black-collared Hawk ^a	Wet-min.	>1000	(0.027, >1000)	5.041	(0.03, >1000)	>1000	(0.012, >1000)
	Dry-max.	>1000	(0.012, >1000)	2.311	(0.013, >1000)	>1000	(0.005, >1000)
Great Black Hawk ^a	Wet-min.	>1000	(0.254, >1000)	6.576	(0.213, >1000)	>1000	(0.176, >1000)
	Dry-max.	>1000	(0.289, >1000)	7.653	(0.235, >1000)	>1000	(0.220, >1000)

^a Estimated only in the Pantanal biome area

Figure 1. Study area, survey transects and the Cerrado and Pantanal domains in the state of Mato Grosso do Sul, Brazil. The Emas National Park on the border with Goiás state is also shown.

Figure 2. Proportion of natural and anthropogenic habitats in the sampled and study areas.

Figure 3. Relative covariate effects on detection probability (p). Logistic regression curves fitted with the (conditional likelihood) AICc-weighted average of the coefficient means and their 90% non-parametric bootstrap confidence intervals (dashed lines) from the detection term of the single abundance covariate models for each species.

Figure 4. Conditional likelihood AICc weights of the single abundance covariate model sets for each species. The height of the bars in each stack is proportional to the AICc weight of the respective model. The values in each bar are the β coefficients of the highest loading (bottom) covariate for each species. No value is presented for the White-tailed Hawk because no covariate had a significantly higher AICc weight. 90% confidence intervals of the β values shown do not overlap 0 (Table 3). “*Cathartes* vultures” group includes Turkey, Lesser Yellow-headed, and unidentified *Cathartes* vulture records.

Discussão geral e Conclusões

Métodos de estimativa de abundância de animais não-marcados: contabilizando a detecção imperfeita

A revisão apresentada examinou como dados de contagens de indivíduos não marcados são influenciados pela detecção imperfeita, e como a consideração desse fenômeno deve informar na escolha do método analítico apropriado para estimativas populacionais. Foram revisados dois métodos já bem estabelecidos (modelos lineares generalizados [GLMs] e amostragem de distância [*distance sampling*]) e nove métodos emergentes que usam modelos hierárquicos baseados em misturas (N-*mixture*; modelo de Royle-Nichols [RN], e N-*mixture* básico, zero inflacionado, espacialmente explícito, visita única, e multiespécies) para estimar a abundância de populações não marcadas, com foco nos seus pré-requisitos e em como cada método lida com a detecção imperfeita e a inflação de zeros.

A detectabilidade é reflexo de características ecológicas, da espécie, do indivíduo e da amostragem. A conspicuidade, o comportamento e a história de vida de uma espécie podem influenciar a detecção, assim como características individuais como sexo, idade e distância até o observador (Iknayan *et al.* 2014). A detecção também pode variar devido a fatores particulares da amostragem, como esforço amostral, clima (e.g., vento, chuva ou neblina), método de amostragem, hora do dia ou período do ano. Pode ainda variar entre locais devido a fatores que influenciam a detecção visual ou auditiva independente do observador, como a estrutura do hábitat (i.e., mata fechada vs. campos abertos) ou ruído de fundo (e.g., vocalizações/sons de outras espécies, cachoeiras, estradas; Alldredge *et al.* 2007). Um outro fator importante que pode influenciar a detecção mas que nem sempre é considerado é a própria abundância de indivíduos no local de amostragem (Tanadini e Schmidt 2011).

1 GLMs são utilizados frequentemente para modelar dados com distribuição diferente
2 da Gaussiana (ou Normal), incluindo contagens (Nelder e Wedderburn 1972). Os GLMs com
3 distribuição de erros Poisson ou binomial-negativa, comumente utilizados para modelar
4 contagens, não são capazes de lidar com a variação nos dados induzida pelo fenômeno da
5 detectabilidade. *Distance sampling* é um método que modela a detectabilidade sob a hipótese
6 de que ela está principalmente relacionada à distância entre o animal e o observador. A
7 distribuição das distâncias medidas para cada observação é utilizada para estimar uma função
8 de detecção, que por sua vez permite estimar a densidade e a abundância (Buckland *et al.*
9 2001), e uma grande vantagem logística do método é que ele requer apenas uma única visita
10 às unidades amostrais para gerar uma estimativa da probabilidade de detecção. Os diversos
11 modelos hierárquicos com base em misturas (*N-mixture*) decompõem explicitamente a
12 variação dos dados em um componente do processo de observação e um componente
13 ecológico (Royle e Dorazio 2008). A estrutura hierárquica básica do método combina um
14 GLM binomial e um GLM com distribuição Poisson ou binomial negativa para modelar os
15 dados de contagem. A detecção é incorporada no componente da observação (o GLM
16 binomial), enquanto que o processo ecológico da abundância é incorporado pelo outro
17 componente. Essa classe de modelos em geral requer amostras replicadas temporalmente em
18 múltiplos locais, e assume que a população é fechada para mortalidade, recrutamento e
19 imigração/emigração entre amostragens. Variações da estrutura básica permitem a
20 incorporação de fenômenos que induzem variabilidade em dados de amostragem, como
21 ocupação/não-ocupação (Wenger e Freeman 2008, Joseph *et al.* 2009), emigração temporária
22 (Chandler *et al.* 2011), detecção correlacionada de indivíduos (Martin *et al.* 2011), e
23 dinâmicas populacionais (nascimentos/mortes e imigração/emigração, Dail e Madsen 2011),
24 e também dados com uma única visita (Sólymos *et al.* 2012). Finalmente, modelos de
25 abundância multiespécies são uma extensão dos modelos de abundância *N-mixture* de visitas

múltiplas, que, através da adição de um componente hierárquico da comunidade (além dos componentes da detecção e da abundância), permitem a estimativa do número de espécies não detectadas, assim como da riqueza, diversidade e similaridade na comunidade (Yamaura *et al.* 2011; Iknayan *et al.* 2014).

Quando avaliado através de dados simulados, o desempenho dos métodos de estimativa de abundância que levam em conta a detectabilidade é geralmente bom (e.g., Royle e Nichols 2003, Royle 2004, Dail e Madsen 2011, Chandler *et al.* 2011), com estimativas (da abundância e outros parâmetros) pouco enviesadas, exceto quando a probabilidade de detecção é muito baixa e o número de sítios e visitas de amostragem é pequeno. O viés causado pelo baixo tamanho amostral, no entanto, pode ser compensado por um número maior de visitas à cada local (de 3 à 5-10), ou se a espécie possui alta probabilidade de detecção ($> 0,3$, Royle e Nichols 2003). Uma outra alternativa para quando o tamanho amostral é baixo é utilizar a mediana ou a moda do estimador de abundância no lugar da média (Royle 2004). Os resultados dos poucos estudos que utilizaram dados reais para comparar diferentes métodos para estimar tamanho populacional apontam que as estimativas de abundância geradas pelos modelos baseados em misturas foram maiores que aquelas geradas por mapeamento de territórios para aves (Kéry, Royle & Schmid 2005) e por captura-recaptura e *distance sampling* para quelônios (Zylstra, Steidl & Swann 2010; Couturier *et al.* 2013), mas não quando comparadas com aquelas geradas por observação direta de lagartos (Doré *et al.* 2011). Os modelos baseados em misturas também tiveram menor precisão (i.e., maior intervalo de confiança) do que captura-recaptura e *distance sampling*, o que não é surpreendente, já que a marcação individual e as medidas de distância utilizadas nesses dois métodos, respectivamente, contribuem com informação adicional para os modelos.

1 *Considerações para desenho amostral e estrutura analítica*

2 Como mencionado anteriormente, devido à estrutura simples, os GLMs com distribuição de
3 erros Poisson ou binomial-negativa não são capazes de contabilizar desvios da distribuição
4 resultantes do excesso de zeros causados pela detecção imperfeita em dados de contagens.
5 Considerando que erros de detecção raramente estão ausentes em dados ecológicos (Martin *et*
6 *al.* 2005), quando o objetivo de uma investigação é obter uma estimativa precisa da
7 abundância (e.g., monitoramentos de populações ameaçadas, estudos de manejo e controle de
8 populações cinegéticas ou invasoras), o uso dessa técnica não é apropriado. Por outro lado,
9 quando o objetivo se limita a fazer inferências sobre os fatores que afetam a abundância
10 relativa, o método pode ser adequado se os fatores investigados não possuírem também um
11 efeito forte sobre a detecção.

12 Os métodos que incorporam estimativas de probabilidade de detecção podem ser
13 divididos entre aqueles que requerem apenas uma visita de amostragem e aqueles que
14 requerem múltiplas visitas. Na maioria dos casos, e especialmente em estudos de populações
15 de vertebrados, as visitas múltiplas de amostragem devem ocorrer em dias diferentes para
16 manter a independência das amostras. Visitar um local em várias datas durante uma
17 campanha de amostragem aumenta os custos de deslocamento e diárias de campo e, para um
18 determinado orçamento, isso reduz o número de locais que podem ser amostrados, podendo
19 assim diminuir a extensão e generalidade do estudo (Lele, Moreno & Bayne 2012). Essa
20 questão pode ser especialmente importante quando se estuda espécies que ocorrem em baixas
21 densidades porque nesses casos é necessário amostrar um grande número de locais para se
22 obter um número suficiente de observações não-nulas para realizar inferências populacionais
23 confiáveis. A demanda conflitante entre o número de visitas e o número de sítios amostrados
24 deve ser considerada cuidadosamente à luz do objetivo do estudo. Monitoramentos de
25 populações em áreas pequenas e médias são um cenário mais adequado para aplicação dos

métodos de múltiplas visitas do que estudos em escalas regionais. Para estes, métodos de visita única pode ser uma opção de melhor custo-benefício.

Os métodos de visita única substituem as visitas repetidas por dados auxiliares para estimar a probabilidade de detecção. Desse grupo, o método mais amplamente utilizado é *distance sampling*, que assume que as medidas de distância ao observador são obtidas com erro mínimo (Buckland *et al.* 2001). Na prática, pode ser difícil obter essas medidas com exatidão quando as amostragens dependem de detecção acústica ou se elas incluem uma grande proporção de indivíduos em movimento (e.g., aves em voo). Para ilustrar, pode-se citar dados de amostragem para 10 espécies comuns de aves de rapina detectadas durante transecções em habitats abertos no Mato Grosso do sul (Dénès *et al.* *dados não publicados*). Em oito das dez espécies, mais de 20% dos indivíduos estavam voando quando detectados, o que sugere que uma grande proporção das medidas de distância ao observador podem não ser confiáveis para estimativas com *distance sampling*. Logo, uma avaliação preliminar do modo de detecção (e.g., razão entre detecções de indivíduos parados/em deslocamento ou visuais/acústicas) pode ser útil no planejamento de um estudo antes da decisão de empregar o método de *distance sampling*.

A realização de amostragens ao longo de estradas, trilhas e rios é comum, especialmente aquelas que focam em espécies de grande porte e/ou de alta mobilidade (e.g., aves de rapina, psitacídeos, aves aquáticas), devido à facilidade de acesso e à limitações logísticas (Buckland *et al.* 2008). Diversos fatores podem levar à densidade de indivíduos atípica ao longo dessas feições, como maior frequência de poleiros (e.g., linhas de transmissão e telefone, cercas, sinais de trânsito, etc.), comida para espécies carniceiras (e.g., animais atropelados), e maior quantidade de hábitat de borda (Buckland *et al.* 2008). Embora esses fatores sejam problemáticos para qualquer análise/método quando extrapolando para uma área mais ampla, *distance sampling* é especialmente vulnerável devido à grande

dependência do método na distribuição espacial dos indivíduos nas cercanias do ponto ou linha de amostragem. Alternativas para a delimitação de unidade amostrais para lidar com esse problema já foram sugeridas, como o posicionamento perpendicular de pontos ou transecções com relação a estradas/trilhas/rios (Buckland *et al.* 2008), mas sua execução nem sempre é factível ou viável logisticamente, pelos mesmos motivos que levam à escolha inicial de tais locais para amostragens. Nessas situações, talvez seja melhor substituir *distance sampling* por outro método de visita única para modelar dados de contagens.

O método N-*mixture* para amostragens com uma única visita (Sólymos *et al.* 2012) requer o uso de covariáveis quantitativas que influenciem a detecção e a abundância separadamente, sendo necessário pelo menos uma variável exclusiva para cada componente hierárquico. A maioria dos estudos e monitoramentos populacionais é desenhada para comparar a abundância entre locais, condições ou períodos distintos e já coleta dados de covariáveis. Informações sobre a hora do dia, clima, habitat e observador, por exemplo, são frequentemente coletados em pesquisas de contagem. Ainda, se covariáveis importantes de abundância e detecção não forem coletadas e incorporadas nos modelos, estimativas de abundância provavelmente serão enviesadas independente do número de visitas (Sólymos *et al.* 2012) e, portanto, esse pré-requisito não pode ser visto como uma objeção ao uso do método. Quando a logística da amostragem ou o orçamento prejudicam ou impedem o uso de *distance sampling* ou métodos N-*mixture* de múltiplas visitas, o método de visita única é uma alternativa para modelar a abundância e a detectabilidade.

Alguns autores sugerem contabilizar o número de unidade amostrais ocupadas em vez do número de indivíduos presentes para reduzir os esforços e custos de monitoramentos (MacKenzie *et al.* 2002, Royle e Nichols 2003). Seguindo essa ideia, o modelo de Royle-Nichols pressupõe que a detecção é dependente da abundância e usa dados de detecção/não-detecção (ao invés de contagens) em múltiplas visitas para gerar estimativas de abundância

(Royle e Nichols 2003). O método é especialmente útil em situações onde os dados disponíveis se limitam a padrões de detecção/não-deteção (e.g., monitoramentos de espécies muito raras ou de difícil detecção onde dificilmente são detectados múltiplos indivíduos por unidade amostral), ou quando os dados são contagens mas não é possível garantir que indivíduos foram contados apenas uma vez durante uma visita – o emprego do método nessa situação requer apenas a simplificação da contagem para detecção/não-deteção.

Quando é possível realizar contagens confiáveis replicadas temporalmente, os diferentes métodos de *N-mixture* de visitas múltiplas permitem a pesquisadores modelarem não apenas a abundância e a detecção, mas fenômenos adicionais como ocupação/não-ocupação (Wenger e Freeman 2008, Joseph et al. 2009), emigração temporária (Chandler *et al.* 2011), detecção correlacionada de indivíduos (Martin *et al.* 2011), e dinâmicas populacionais (nascimentos/mortes e imigração/emigração, Dail e Madsen 2011). Tal versatilidade deve encorajar a coleta de dados de contagens com múltiplas visitas quando o sistema em estudo e o orçamento de pesquisa permitirem.

Recentemente, Banks-Leite et al. (2014) questionaram o uso de modelos que incorporam a detecção imperfeita para modelar a abundância de uma espécie em comunidades dominadas por espécies raras, como florestas tropicais, devido à necessidade de altas probabilidades de detecção/recaptura, que dificilmente são obtidas para tais espécies. Os modelos *N-mixture* multiespécies usam dados de contagens (ou detecção/não-deteção) das espécies comuns e raras para gerar uma distribuição da abundância (ou ocupação) e da probabilidade de detecção no nível da comunidade, a partir da qual é possível obter estimativas para cada espécie, incluindo as mais raras (Iknayan *et al.* 2014). Esse “compartilhamento de informações” permite o uso mais eficiente dos dados do que em modelos de uma única espécie, melhorando as estimativas. A grande vantagem dessa metodologia, cuja aplicação até o momento é restrita a dados com múltiplas visitas, é a

1 habilidade de combinar estimativas de abundância e riqueza e ao mesmo tempo incorporar o
2 fenômeno da detecção imperfeita. No entanto, esse tipo de modelo hierárquico ainda é
3 relativamente novo, e suas limitações e desempenho precisam ser avaliados mais
4 amplamente. Ainda, a implementação dos modelos é relativamente complexa e além da
5 capacidade de programação de muitos usuários em potencial, embora exemplos de código e
6 programas para sua execução estejam disponíveis gratuitamente na Internet (Iknayan *et al.*
7 2014).

8

9 **Abundância de aves de rapina no Cerrado e Pantanal do MS e os efeitos da degradação** 10 **de hábitat: perspectivas com métodos baseados na detectabilidade**

11 A protocolo de campo de visita única e o uso de um modelo de abundância tipo *N-mixture*
12 para dados de visita única com inflação-de-zeros e detecção imperfeita (Sólymos *et al.* 2012)
13 permitiram a amostragem em escala regional que rendeu estimativas de abundância em
14 função de covariáveis ambientais para doze espécies de aves de rapina, levando em conta a
15 detecção imperfeita, apesar da ausência de replicas temporais. Assim, foi possível investigar
16 como mudanças de hábitat, estação (i.e., seca vs. chuvosa) e nível de elevação da superfície
17 dos rios (como uma medida do grau de alagamento no Pantanal) afetaram a abundância de
18 aves de rapina, e gerar projeções da abundância para a área de estudo. Aspectos
19 metodológicos e biológicos dos resultados são discutidos abaixo.

20

21 *Considerações metodológicas*

22 A alta frequência de zeros observados nas contagens (i.e., inflação-de-zeros) é indicativa de
23 diversos processos resultando em não-detectões. Modelos de abundância do tipo *N-mixture*
24 discernem zeros que são produto da detecção imperfeita (onde a abundância real é maior que
25 zero mas a contagem é 0) de zeros devidos ao processo ecológico da abundância (onde tanto

a abundância quanto a contagem são iguais a 0). Estudos que utilizaram a variante zero-inflacionada dos modelos *N-mixture* distinguem ainda um outro tipo de zero que é devido à existência de unidades amostrais não-ocupadas, ou seja, fora da área de ocorrência da espécie (Wenger e Freeman 2008, Joseph et al. 2009). Embora as espécies de aves de rapina contempladas neste estudo possuam áreas de distribuição geográfica muito amplas e possam ocorrer ao longo de toda área de estudo (Ferguson-Lees e Christie 2001), em uma escala menor a sua ocorrência pode ser esporádica de modo que zeros adicionais causados por “não-ocupação” também devem ocorrer. Contudo, pode também haver um outro tipo de zero resultante das ausências temporárias, já que aves de rapina possuem alta mobilidade e podem usar um local regularmente mas não serem detectadas no momento da amostragem por estarem visitando uma parte da sua área de vida fora da unidade amostral. Uma vez que os esses dois mecanismos provavelmente contribuem para o excesso de zeros na contagem, não é possível decompor a probabilidade de inflação-de-zeros estimada pelos modelos para cada processo. Logo, inferências ecológicas a respeito desse parâmetro foram evitadas, e o foco foi mantido nos parâmetros de abundância e probabilidade de detecção.

O uso modelos *N-mixture* com distribuição binomial negativa zero-inflacionada (ZINB) para dados com excesso de zeros tem sido criticado com base no fato de que eles comumente resultam em estimativas irrealistas dos parâmetros, apesar de serem frequentemente considerados como o “melhor modelo” quando comparados com modelos com distribuições Poisson ou Poisson zero-inflacionada (ZIP; Kéry et al. 2005, Joseph et al. 2009). Joseph et al. (2009) sugerem que os modelos *N-mixture* ZINB podem gerar estimativas muito grandes de abundância ao estimarem probabilidades de detecção individual excessivamente baixas. O uso de modelos ZINB ao invés de ZIP para o Urubu-de-cabeça-vermelha, Urubu-de-cabeça-amarela, Urubu-de-cabeça-preta, Gavião-caramujeiro e Caracará no presente trabalho se justifica pelo fato de que essas espécies são frequentemente

1 detectadas em grandes grupos, o que cria uma fonte adicional de variação nos dados. Assim,
2 a distribuição ZINB foi utilizada para modelar esse fenômeno adicional, e não como um meio
3 de obter melhor ajuste dos modelos a despeito de realismo ecológico. As estimativas de
4 abundância obtidas com os modelos ZINB aparentam ser razoáveis e mais conservadoras do
5 que aquelas obtidas com modelos ZIP para as espécies que não se agregam, e as
6 probabilidade de detecção estimadas não são irrealisticamente baixas.

7 As projeções de abundância são uma primeira tentativa de gerar mapas regionais dos
8 padrões de abundância de aves de rapina no Cerrado e Pantanal com base em transecções
9 com veículos em estradas (*road-surveys*) corrigidas para erros de detecção. Como
10 mencionado anteriormente, um grande número de vieses intrínsecos das *road-surveys* podem
11 influenciar a abundância de aves de rapina, incluindo maior frequência de poleiros, mais
12 alimentos para espécies carniceiras e maior quantidade de hábitat de borda (Fuller e Mosher
13 1981, Millsap e Jr 1988, Meunier e Verheyden 2000, Carrete et al. 2009). Adicionalmente, a
14 distribuição espacial das transecções foi limitada pela disponibilidade de estradas, o que
15 resultou em amplas áreas sub-amostradas (e.g., o noroeste do estado). Esses fatores podem ter
16 influenciado as projeções de abundância pela baixa representatividade de alguns tipo de
17 hábitat, como vegetações naturais mais preservadas do Cerrado e principalmente do Pantanal.
18 Ainda, métodos de inferência com base em verossimilhança não funcionam bem com
19 pequenas amostras (Royle e Nichols 2003), então é provável que as predições de abundância
20 das espécies com menos registros (<200, Gavião-belo, Gavião-preto, Gavião-de-rabo-branco,
21 Falcão-de-coleira) sejam menos confiáveis do que as das espécies mais comuns (as três
22 espécies de urubus, Gavião-caboclo, Gavião-caramujeiro, Gavião-carijó, Caracarás e
23 Quiriquiri). Com essas advertências, os mapas apresentados devem ser considerados como
24 aproximações da variação espacial e sazonal da abundância, ao invés de representações reais
25 do número de indivíduos que ocorrem na região.

1

2 *Considerações biológicas*

3 Embora uma investigação sistemática dos fatores que potencialmente influenciam a detecção
4 de aves de rapina esteja além do escopo desse trabalho, a análise dos coeficientes de detecção
5 estimados pelos modelos de abundância permite o reconhecimento de padrões gerais.
6 Costuma-se relacionar a detecção de aves de rapina a padrões de atividade, que por sua vez
7 variam ao longo do dia devido a mudanças na disponibilidade de presas ou condições de voo
8 (Bunn, Klein & Bildstein 1995). Por exemplo, espécies que caçam pequenos mamíferos ou
9 aves são mais ativas no início da manhã do que no fim da manhã e à tarde porque a atividade
10 dessas presas geralmente tem seu pico no amanhecer (Vieira e Baumgarten 1995, Halle
11 1995), enquanto que espécies que caçam répteis apresentam o pico de atividade mais tarde
12 (Blair 2009). Urubus e outras aves de rapina de grande porte que necessitam de térmicas e
13 correntes ascendentes para planar têm dificuldade para voar no começo da manhã, sendo
14 mais ativos após esse período (Fuller e Mosher 1981).

15 Os padrões de detecção observados corroboram essas generalizações. Foi verificado
16 um efeito negativo da hora do dia na detecção do Gavião-caboclo, Gavião-de-rabo-branco,
17 Gavião-carijó, Caracará e Falcão-de-coleira, espécies que se alimentam de mamíferos, répteis
18 e aves. A dieta do quiriquiri no Cerrado é dominada por artrópodes (>95% das presas),
19 distribuídos igualmente entre espécies diurnas e noturnas. Isso sugere que esse falcão caça
20 nas horas crepusculares (Cabral, Granzinoli & Motta-Junior 2006), o que pode explicar a
21 detecção reduzida dessa espécie no início da tarde. Uma parte importante da dieta do Gavião-
22 Belo e do Gavião-Preto consiste de peixes e outros animais aquáticos (e.g., anfíbios,
23 carangueijos). Embora o período de atividade de peixes de água doce seja bem variável,
24 muitas espécies são mais ativas quando a temperatura da água é mais alta (Bizzotto *et al.*
25 2009), o que pode explicar o efeito positivo da hora do dia na detecção desses dois gaviões

no Pantanal. Em contraste, a detecção do Gavião-caramujeiro foi maior durante o meio do dia e início da tarde, horários onde o comportamento de empoleiramento (i.e., quando os animais permanecem em poleiros descansando e/ou caçando à espreita oportunisticamente) tem seu pico para essa espécie (Beissinger 1983). Portanto, comportamentos que aumentam a exposição e consequentemente a detecção não são necessariamente ligados à maior mobilidade. No entanto, a hora do dia não afetou a detecção das três espécies de urubu como esperado; o urubu-de-cabeça-vermelha e o urubu-de-cabeça-amarela foram mais detectáveis no início do dia do que mais tarde, enquanto que a detecção do urubu-de-cabeça-preta foi menor no meio do dia. O deslocamento do pico de atividade para um período mais cedo pode ser consequência de térmicas estarem disponíveis mais cedo em regiões tropicais do que nas áreas temperadas, onde padrões de detecção foram estudados anteriormente (Bunn *et al.* 1995; Vergara 2010). Por outro lado, a observação de dormitórios coletivos, geralmente em poleiros bem expostos na área de estudo, pode também aumentar a detecção no início e no fim do dia, apesar da baixa atividade.

Surpreendentemente, a quantidade de vegetação fechada foi um fator importante para detecção apenas para o Urubu-de-cabeça-preta e o Gavião-belo, com efeito negativo, e para o Urubu-de-cabeça-vermelha e o Quiriquiri, com efeito positivo. Embora a visibilidade em habitats fechados é inegavelmente menor (Fuller e Mosher 1981), poleiros nas suas bordas – frequentemente associados a estradas – são comumente utilizados por aves de rapina para descansar, caçar e atividades de manutenção (arrumação e limpeza da plumagem [*preening*], banhos de sol para termo-regulação, etc.). Isso pode aumentar a detecção em ambientes fechados em comparação àqueles abertos, como campos, plantações e pastagens sem essas feições. Que a detecção de Urubus-de-cabeça-vermelha foi positivamente influenciada pela quantidade de carcaças enfatiza a importância desse recurso, não apenas como alimento (Fig. 1), mas também como armadilha ecológica. Urubus que pousam em estradas nem sempre

1 conseguem evitar veículos em alta velocidade. De fato, carcaças de quatro Urubus-de-
2 cabeça-preta, dois Urubus-de-cabeça-vermelha (Fig. 2) e seis Cararacás foram encontradas
3 durante as amostragens, provavelmente vítimas de colisões com veículos. Esse tipo de
4 mortalidade é frequente no Cerrado e no Pantanal (Fischer *et al.* 2003).

5 Apesar da natureza altamente sazonal do Cerrado e do Pantanal, apenas a abundância
6 do Quiriquiri e do Gavião-caramujeiro foram afetadas pela época de amostragem e enchente
7 sazonal, respectivamente. A estação chuvosa no Cerrado e Pantanal coincide em boa parte
8 com ao período reprodutivo do Quiriquiri na América do Sul (Outubro-Março, Ferguson-
9 Lees e Christie 2001), e as amostragens de estação chuvosa foram realizadas ao fim desse
10 período (fim de Janeiro-início de Fevereiro). Isso, combinado com um período de
11 dependência dos juvenis que pode durar mais de um mês (Ferguson-Lees e Christie 2001) e
12 uma plumagem juvenil que não é facilmente distinguível da adulta na raça local (*F. s.*
13 *cinnamominus*) pode explicar a maior abundância na estação chuvosa, quando ocorre a
14 reprodução. Por outro lado, sabe-se que o Gavião-caramujeiro realiza movimentos em
15 resposta a eventos sazonais como secas, cheias e emergência de caramujos (Bennetts e
16 Kitchens 2000, Mooij *et al.* 2002, Darby *et al.* 2002), o que explica a forte correlação entre a
17 abundância dessa espécie e altos níveis de cheia no Pantanal.

18 A proporção de hábitat do cerrado e de mata ciliar, com efeito positivo, foram os dois
19 melhores preditores para a abundância do Gavião-caboclo e do Gavião-preto,
20 respectivamente, confirmando as expectativas de requerimento de habitat para essas duas
21 espécies (Ferguson-Lees e Christie 2001, Carrete *et al.* 2009). A abundância do Gavião-belo
22 foi negativamente afetada por habitat florestal, provavelmente devido à forte associação da
23 espécie com rios e lagoas, onde forrageia. Florestas no Pantanal tendem a ocorrer apenas em
24 áreas de maior elevação que não estão sujeitas à inundação (Junk *et al.* 2006).

As respostas espécie-específicas de aves de rapina à transformação de hábitat podem ser variáveis e dependentes do contexto (Sergio *et al.* 2008). Os resultados obtidos demonstram que a abundância da maior parte das espécies foi negativamente influenciada pela conversão de habitats naturais do Cerrado e Pantanal a usos antrópicos, até mesmo para espécies generalistas que costumam ser consideradas como indicadores ruins da qualidade de habitats (e.g., Urubu-de-cabeça-vermelha, Urubu-de-cabeça-preta, Caracará; Rodríguez-estrella *et al.* 1998, Zilio *et al.* 2013). No estado do MS, a maior parte do Cerrado original foi convertida em pastagens, plantações de soja e cana-de-açúcar e outros habitats antrópicos (Silva *et al.* 2011). Adicionalmente, a conversão dos habitats naturais em pastagens e plantações no Cerrado levou a erosão intensa, causando deposição de sedimentos na bacia do Pantanal e alterando padrões de fluxo de água e regimes hidrológicos (Harris *et al.* 2005).

O Brasil é o país com o maior rebanho bovino, e é também o maior exportador de carne bovina do mundo (McAlpine *et al.* 2009). No entanto, metade das pastagens plantadas no domínio do Cerrado estão degradadas e sustentam pouco gado devido à cobertura vegetal reduzida, invasão por plantas não palatáveis e cupinzeiros (Costa e Rehman 2005, Klink e Machado 2005). A quantidade de pastagens foi forte e negativamente relacionada à abundância de Urubu-de-cabeça-vermelha, Urubu-de-cabeça-amarela, Urubu-de-cabeça-preta, Caracará, Falcão-de-coleira, Gavião-caboclo e Gavião-caramujeiro. Tubelis e Cavalcanti (2000) verificaram, para Passeriformes do Cerrado, que a abundância em pastagens é menor que aquela observada em habitats naturais, e a comunidade apresenta forte dissimilaridade entre os esses ambientes. A conversão de habitats naturais no Cerrado para pastagens plantadas pode reduzir a precipitação local em até 10%, e aumentar a duração de estiagens e a temperatura média da superfície em 0,5 °C (Hoffmann e Jackson 2000). Ainda, pastagens no Cerrado e no Pantanal possuem riqueza muito baixa de plantas herbáceas, frequentemente dominada por uma única espécie exótica (e.g., *Brachiaria* sp.), em contraste

1 com a alta riqueza de espécies encontrada nos campos naturais (Filgueiras 1991; Junk *et al.*
2 2006). Esse efeito, combinado com um empobrecimento similar da fauna de invertebrados e
3 pequenos vertebrados, pode contribuir na redução da abundância de aves de rapina. De
4 maneira semelhante, a escassez de arbustos e árvores decorrente da conversão em pastagens
5 de habitats florestais ou savânicos, como o cerrado, cerrado *sensu strictu*, e chaco,
6 provavelmente causa a perda de recursos e sítios para nidificação e caça, e de locais de
7 dormitório, resultando numa menor capacidade de suporte.

8 Carvalho et al. (2009) demonstraram que, no Cerrado, a área remanescente de
9 vegetação natural em paisagens dominadas por plantações é semelhante a de paisagens
10 dominadas por pastagens. Os cultivos de soja e cana-de-açúcar se tornaram poderosas
11 ameaças aos habitats naturais do Cerrado em decorrência do desenvolvimento de cultivares
12 mais tolerantes, do *lobby* e subsídios governamentais intensos, e da crescente demanda por
13 biocombustíveis (e.g., biodiesel e etanol) como fontes energéticas alternativas (Fearnside
14 2002; Carvalho *et al.* 2009). Plantações de soja e cana-de-açúcar necessitam de um grande
15 investimento de capital e maquinário, preparação do solo e insumos, sendo que a fertilidade
16 do solo e a topografia são os principais fatores limitantes da implantação desse tipo de
17 agricultura mecanizada. Consequentemente, os principais empreendedores desses cultivos
18 são as grandes empresas de agronegócio, ao invés de pequenos agricultores. Essas plantações
19 geralmente se estabelecem em áreas onde a vegetação natural original já foi removida,
20 geralmente pastagens de propriedade de pequenos agricultores, que então se deslocam para
21 áreas da fronteira agrícola onde continuam o ciclo removendo mais habitat natural. O
22 impacto dessas plantações é ainda maior devido à vasta infraestrutura necessária para colheita
23 e transporte (Fearnside 2002). De fato, Granzinoli (2009) observou, em um estudo de
24 seleção de habitat, que as aves de rapina no Cerrado de São Paulo rejeitaram monoculturas,
25 especialmente cana-de-açúcar, consistentemente. A baixa representatividade desse tipo de

uso do solo nos dados de hábitat utilizados, assim como plantações de eucalipto, e áreas urbanas e de vegetação secundária, é uma consequência da pequena proporção desses habitats na área de estudo e de opções de rotas de transecção limitadas. Isso pode ter reduzido a importância desses habitats como preditores da abundância de boa parte das espécies analisadas, e contribuído para os grandes intervalos de confiança observados. Não obstante, esses habitats antrópicos tiveram em geral um efeito negativo na abundância de aves de rapina.

Conclusões

Estudos de monitoramento de populações e avaliações de respostas a mudanças ambientais com a meta de informar ações de conservação e decisões de manejo precisam estimar rigorosamente a abundância e como ela é influenciada por múltiplos fatores. Isso envolve reconhecer que, independente da experiência do observador, contagens de animais estão sujeitas a erros de detecção e outros processos que causam inflação de zeros nos dados. Portanto, é necessária a adoção de um desenho amostral e um método analítico para estimativas populacionais que levem em conta esses fenômenos. Dos 11 métodos analíticos para estimativa populacional revisados no presente trabalho, oito são capazes de lidar com a detecção imperfeita e outras fontes de variação em contagens como a não-ocupação, emigração temporária, detecção correlacionada e dinâmica populacional. Todos eles foram desenvolvidos na última década, e sua eficiência ainda está sendo avaliada. Espera-se que novos desenvolvimentos continuem a surgir nessa importante área da estatística ecológica.

Métodos para estimativa populacional variam no grau de adequação à projetos de pesquisa, dependendo do táxon amostrado, se amostragens são realizadas para uma ou múltiplas espécies, da disponibilidade e exequibilidade da coleta de dados auxiliares (covariáveis), e da escala e objetivos do estudo. Os métodos também impõem custos

1 financeiros e logísticos diferentes, dependendo da necessidade de visitas de amostragem
2 repetidas. Pesquisadores devem estar cientes dessas diferenças ao planejarem estudos para
3 que esforços e verbas sejam utilizados eficientemente.

4 Os resultados do estudo de caso demonstram que as populações de aves de rapina
5 foram significativamente impactadas pela degradação dos habitats naturais no Cerrado e
6 Pantanal do MS, inclusive para espécies consideradas generalistas de habitat. Esses
7 resultados concordam com o observado em outros habitats neotropicais (Carrete *et al.* 2009).
8 Logo, a proteção dos habitats naturais remanescentes é essencial para prevenir um declínio
9 ainda maior das populações de aves de rapina no MS. Embora nenhuma das espécies
10 investigadas no presente estudo seja classificada como ameaçada, foram registradas, em
11 números insuficientes para inclusão na análise, outras 21 espécies de aves de rapina,
12 incluindo o raro Urubu-rei (*Sarcorhamphus papa*), a ameaçada Águia-cinzenta
13 (*Harpyhaliaetus coronatus*) e espécies migratórias como a Águia-pescadora (*Pandion*
14 *haliaetus*) e o Falcão-peregrino (*Falco peregrinus*). Essas espécies provavelmente estão
15 sujeitas a pressões semelhantes na área de estudo.

Figura 1. Urubu-de-cabeça-vermelha (*Cathartes aura*) se alimentando de carcaça de Mão-pelada (*Procyon cancrivorus*) atropelado na rodovia BR-262 próximo à Corumbá, MS.

Figura 2. Carcaça de Urubu-de-cabeça-vermelha (*Cathartes aura*) atropelado na rodovia BR-262 próximo à Miranda, MS.

Resumo

A urbanização e a expansão das fronteiras agrícolas na região Neotropical estão entre as principais forças causadoras da degradação ambiental em habitats abertos naturais. Inferências e estimativas de abundância são críticas para quantificação de dinâmicas populacionais e impactos de mudanças ambientais. Contudo, a detecção imperfeita e outros fenômenos que causam inflação de zeros podem induzir erros de estimativas e dificultar a identificação de padrões ecológicos. Examinamos como a consideração desses fenômenos em dados de contagens de indivíduos não marcados pode informar na escolha do método apropriado para estimativas populacionais. Revisamos métodos estabelecidos (modelos lineares generalizados [GLMs] e amostragem de distância [*distance sampling*]) e emergentes que usam modelos hierárquicos baseados em misturas (*N-mixture*; modelo de Royle-Nichols [RN], e *N-mixture* básico, zero inflacionado, espacialmente explícito, visita única, e multiespécies) para estimar a abundância de populações não marcadas. Como estudo de caso, aplicamos o método *N-mixture* baseado em visitas únicas para modelar dados de contagens de aves de rapina em estradas e investigar como transformações de habitat no Cerrado e Pantanal do Mato Grosso do Sul afetaram as populações de 12 espécies em uma escala regional ($>300.000 \text{ km}^2$). Os métodos diferem nos pré-requisitos de desenho amostral, e a sua adequabilidade depender da espécie em questão, da escala e objetivos do estudo, e considerações financeiras e logísticas, que devem ser avaliados para que verbas, tempo e esforço sejam utilizados com eficiência. No estudo de caso, a detecção de todas as espécies foi influenciada pelo horário de amostragem, com efeitos congruentes com expectativas baseadas no comportamento de forrageamento e de voo. A vegetação fechada e carcaças também influenciaram a detecção de algumas espécies. A abundância da maioria das espécies foi negativamente influenciada pela conversão de habitats naturais para antrópicos, particularmente pastagens e plantações de soja e cana-de-açúcar, até mesmo para espécies generalistas consideradas como indicadores ruins da qualidade de habitats. A proteção dos habitats naturais remanescentes é essencial para prevenir um declínio ainda maior das populações de aves de rapina na área de estudo, especialmente no domínio do Cerrado.

Abstract

Urbanization and the expansion of agricultural frontiers are among the main forces driving the degradation of natural habitats in Neotropical open habitats. Inference and estimates of abundance are critical for quantifying population dynamics and the impacts of environmental change. Yet imperfect detection and other phenomena that cause zero inflation can induce estimation error and obscure ecological patterns. We examine how detection error and zero-inflation in count data of unmarked individuals inform the choice of analytical method for estimating population size. We review established (GLMs and distance sampling) and emerging methods that use *N*-mixture models (Royle-Nichols model, and basic, zero-inflated, temporary emigration, beta-binomial, generalized open-population, spatially explicit, single-visit and multispecies) to estimate abundance of unmarked populations. As a case study, we employed a single visit *N*-mixture approach to model roadside raptor count data and investigate how land-use transformations in the Cerrado and Pantanal domains in Brazil have affected the populations of 12 species on a regional scale ($>300,000 \text{ km}^2$). Methods differ in sampling design requirements, and their suitability will depend on the study species, scale and objectives of the study, and financial and logistical considerations, which should be evaluated to use funds, time and effort efficiently. In the case study, detection of all species was influenced by time of day, with effects that follow expectations based on foraging and flying behavior. Closed vegetation on and carcasses found during surveys also influenced detection of some species. Abundance of most species was negatively influenced by conversion of natural Cerrado and Pantanal habitats to anthropogenic uses, particularly pastures, soybean and sugar cane plantations, even for generalist species usually considered poor habitat-quality indicators. Protection of the remaining natural habitats is essential to prevent further decline of raptor populations in the study area, especially in the Cerrado domain.

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Apêndices

Os apêndices abaixo são todos referentes ao capítulo 2 (*Raptor abundance in the Brazilian Cerrado and Pantanal: insights from single-visit detection-based methods for survey data*).

Para manter consistência com o texto de referência, os anexos estão em inglês.

Appendix A

Count frequency plots for each species. “*Cathartes* vultures” includes records of Turkey, Lesser-yellow-headed and unidentified *Cathartes* vultures. Counts of the Black-collared Hawk, Great Black Hawk and Snail Kite are from within the Pantanal biome only.

Appendix B

Results of the conditional likelihood AICc selection on the detection term for each species. “*Cathartes* vultures” group includes records of Turkey, Lesser Yellow-headed, and unidentified *Cathartes* vultures. p is detection probability. Models include all abundance covariates (not shown, see Table 2 in text). Detection covariates of the models in bold are those selected for the rest of the analysis.

Species	Detection covariates	p	AICc	dAICc	Weight
Turkey Vulture	Time, closed habitat, carcasses	0.81	1709.3	0.0	0.295
	Time, time ² , closed habitat, carcasses	0.71	1709.6	0.2	0.260
	Time, carcasses	0.51	1710.7	1.4	0.150
	Time, time ² , carcasses	0.35	1711.3	2.0	0.107
	Time, time ² , closed habitat	0.34	1712.2	2.9	0.070
	Time	0.71	1712.5	3.2	0.060
	Time, closed habitat	0.51	1713.7	4.4	0.032
	Time, time ²	0.72	1714.2	4.9	0.025
	Closed habitat, carcasses	0.44	1751.5	42.2	<0.001
	Carcasses	0.57	1753.9	44.6	<0.001
	Closed habitat	0.37	1758.2	48.9	<0.001
Lesser Yellow-headed Vulture	Time	0.33	355.3	0.0	0.312
	Time, closed habitat	0.37	356.3	1.0	0.189
	Time, time ²	0.72	356.6	1.2	0.168
	Time, time ² , closed habitat	0.55	357.1	1.8	0.126
	Time, carcasses	0.46	357.5	2.2	0.105
	Time, closed habitat, carcasses	0.41	358.7	3.4	0.057
	Time, time ² , closed habitat, carcasses	0.53	359.4	4.0	0.042
	Time, time ² , carcasses	0.40	368.5	13.1	<0.001
	Carcasses	0.39	372.4	17.1	<0.001
	Closed habitat	0.94	373.3	18.0	<0.001
	Closed habitat, carcasses	0.47	373.3	18.0	<0.001
<i>Cathartes</i> vultures	Time, closed habitat	0.60	3418.3	0.0	0.355
	Time, closed habitat, carcasses	0.73	3419.0	0.7	0.254
	Time, time ² , closed habitat	0.74	3420.2	2.0	0.133
	Time	0.69	3420.9	2.6	0.096
	Time, time ² , closed habitat, carcasses	0.76	3421.6	3.3	0.069
	Time, carcasses	0.68	3422.2	3.9	0.051
	Time, time ²	0.69	3423.3	5.0	0.029
	Time, time ² , carcasses	0.74	3424.8	6.5	0.014
	Closed habitat	0.32	3495.5	77.2	<0.001
	Closed habitat, carcasses	0.76	3495.6	77.3	<0.001
	Carcasses	0.78	3496.5	78.2	<0.001
Black Vulture	Time, time², closed habitat	0.54	2302.8	0.0	0.599
	Time, time ² , carcasses	0.49	2304.2	1.4	0.296
	Time, time ² , closed habitat, carcasses	0.66	2306.6	3.8	0.088
	Time, time ²	0.42	2311.2	8.4	0.009

	Time, carcasses	0.66	2311.6	8.9	0.007
	Time, closed habitat, carcasses	0.65	2315.2	12.4	0.001
	Time, closed habitat	0.67	2321.4	18.6	<0.001
	Time	0.32	2322.7	20.0	<0.001
	Closed habitat, carcasses	0.74	2361.9	59.2	<0.001
	Carcasses	0.52	2367.2	64.4	<0.001
	Closed habitat	0.56	2372.0	69.3	<0.001
Southern Crested-Caracara	Time	0.43	1471.9	0.0	0.395
	Time, carcasses	0.57	1473.7	1.8	0.161
	Time, closed habitat, carcasses	0.44	1474.8	2.9	0.093
	Time, time ² , carcasses	0.52	1474.8	2.9	0.093
	Time, time ²	0.44	1474.9	3.0	0.090
	Time, closed habitat	0.40	1475.0	3.1	0.085
	Time, time ² , closed habitat	0.43	1476.0	4.1	0.051
	Time, time ² , closed habitat, carcasses	0.65	1477.0	5.1	0.031
	Closed habitat	0.48	1506.0	34.1	<0.001
	Closed habitat, carcasses	0.38	1507.7	35.8	<0.001
	Carcasses	0.55	1507.8	35.9	<0.001
	Time	0.79	752.6	0.0	0.390
Savanna Hawk	Time, closed habitat	0.63	752.9	0.3	0.330
	Time, time ²	0.84	754.3	1.7	0.170
	Time, time ² , closed habitat	0.52	755	2.4	0.120
	Closed habitat	0.65	769.9	17.3	<0.001
Roadside Hawk	Time	0.72	311.7	0.0	0.425
	Time, time ²	0.69	311.9	0.3	0.372
	Time, closed habitat	0.24	313.7	2.1	0.151
	Time, time ² , closed habitat	0.78	316.0	4.3	0.050
	Closed habitat	0.39	321.7	10.0	0.003
White-tailed Hawk	Time	0.66	185.9	0.0	0.320
	Closed habitat	0.12	186.4	0.6	0.240
	Time, time ²	0.93	187.3	1.4	0.160
	Time, closed habitat	0.33	187.5	1.6	0.140
	Time, time ² , closed habitat	0.14	187.5	1.6	0.140
American Kestrel	Time, time², closed habitat	0.51	319.3	0.0	0.630
	Time	0.20	321.3	2.0	0.231
	Time, time ²	0.24	322.9	3.6	0.104
	Time, closed habitat	0.25	325.1	5.8	0.035
	Closed habitat	0.39	332.3	13.1	<0.001
Aplomado Falcon	Time	0.36	126.6	0.0	0.370
	Time, closed habitat	0.72	126.7	0.1	0.350
	Time, time ²	0.51	128.2	1.7	0.160
	Time, time ² , closed habitat	0.70	129.2	2.6	0.100
	Closed	0.56	132.4	5.8	0.020
Snail Kite	Time, time²	0.37	160.7	0.0	0.432
	Time	0.86	160.8	0.2	0.398
	Time, closed habitat	0.49	163.9	3.2	0.086

Black-collared Hawk	Time, time ² , closed habitat	0.36	163.9	3.3	0.084
	Closed habitat	0.60	212.8	52.1	<0.001
	Time, closed habitat	0.86	121.1	0.0	0.503
	Time	0.77	123.0	1.8	0.200
	Time, time ²	0.93	123.1	1.9	0.190
	Closed habitat	0.27	124.8	3.7	0.081
	Time, time ² , closed habitat	0.22	127.0	5.9	0.026
	Time	0.71	121.1	0.0	0.430
	Time, closed habitat	0.69	121.8	0.7	0.300
	Time, time ² , closed habitat,	0.84	123.3	2.3	0.138
Great Black Hawk	Time, time ²	0.45	123.8	2.8	0.108
	Closed habitat	0.92	126.8	5.7	0.024

Appendix C

Table 1. Population parameter estimates of the single abundance covariate models of Turkey Vulture (*Cathartes aura*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ samples), where λ is the rate parameter of the NB distribution, $p =$ detection probability, $\phi =$ zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Abundance covariates	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Pasture	342.5	0.0	0.851	λ	1.631	1.80	1.731	(0.970, 2.868)
				p	0.780	0.76	0.808	(0.487, 0.924)
				ϕ	0.120	0.15	0.166	(<0.000, 0.34)
				σ	2.333	557.43	2.145	(1.268, 4.375)
Urban	348.7	6.2	0.039	λ	1.655	1.98	1.761	(1.025, 3.457)
				p	0.752	0.72	0.739	(0.414, 0.926)
				ϕ	0.110	0.16	0.171	(<0.000, 0.336)
				σ	2.412	>1000	2.108	(1.294, 4.164)
Season (wet)	349.8	7.2	0.023	λ	1.633	1.92	1.736	(1.096, 3.495)
				p	0.765	0.72	0.726	(0.408, 0.929)
				ϕ	0.103	0.14	0.144	(<0.000, 0.345)
				σ	2.474	2.56	2.354	(1.376, 4.61)
River level	349.9	7.3	0.022	λ	1.657	1.97	1.790	(0.884, 3.723)
				p	0.720	0.70	0.702	(0.416, 0.926)
				ϕ	0.073	0.14	0.136	(<0.000, 0.331)
				σ	2.586	2.55	2.229	(1.312, 5.134)
Agriculture	350.9	8.3	0.013	λ	1.712	1.93	1.779	(1.012, 3.274)
				p	0.733	0.72	0.732	(0.420, 0.918)
				ϕ	0.111	0.14	0.141	(<0.000, 0.334)
				σ	2.439	2.66	2.350	(1.305, 4.147)
Chaco	351.6	9.1	0.009	λ	1.588	1.78	1.689	(0.882, 2.943)
				p	0.752	0.73	0.756	(0.464, 0.928)
				ϕ	0.074	0.12	0.110	(<0.000, 0.331)
				σ	2.542	>1000	2.360	(1.402, 5.143)
Cerrado	351.7	9.1	0.009	λ	1.539	1.77	1.600	(0.951, 3.086)
				p	0.787	0.76	0.794	(0.452, 0.937)
				ϕ	0.087	0.14	0.133	(<0.000, 0.33)
				σ	2.503	2.61	2.292	(1.379, 4.654)
Cane	351.9	9.4	0.008	λ	1.360	1.54	1.480	(0.876, 2.387)
				p	0.885	0.82	0.878	(0.590, 0.941)
				ϕ	0.080	0.12	0.108	(<0.000, 0.34)
				σ	2.546	>1000	2.362	(1.298, 5.35)
eucalyptus	352.1	9.6	0.007	λ	1.405	1.62	1.527	(0.975, 2.39)
				p	0.859	0.80	0.863	(0.526, 0.936)

Riverine	352.2	9.7	0.007	ϕ	0.082	0.13	0.120	(<0.000, 0.318)
				σ	2.528	2.75	2.330	(1.437, 4.817)
				λ	1.518	1.80	1.722	(0.953, 2.971)
				p	0.790	0.75	0.773	(0.454, 0.927)
				ϕ	0.078	0.14	0.131	(<0.000, 0.337)
				σ	2.543	5.42	2.301	(1.390, 4.276)
Sec. vegetation	352.3	9.7	0.007	λ	1.654	1.86	1.690	(0.946, 3.342)
				p	0.740	0.73	0.744	(0.428, 0.937)
				ϕ	0.096	0.14	0.135	(<0.000, 0.328)
				σ	2.465	>1000	2.260	(1.317, 5.414)
Forest	352.3	9.7	0.007	λ	1.499	1.85	1.737	(0.927, 3.037)
				p	0.797	0.74	0.747	(0.446, 0.932)
				ϕ	0.074	0.15	0.152	(<0.000, 0.348)
				σ	2.569	2.55	2.177	(1.329, 4.67)

Table 2. Population parameter estimates of the single abundance covariate models of Lesser Yellow-headed Vulture (*Cathartes burrovianus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ samples), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma=0$ is the Poisson case).

Abundance covariates	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Pasture	342.5	0.0	0.851	λ	2.059	2.008	2.019	(0.703, 3.401)
				p	0.342	0.422	0.363	(0.261, 0.82)
				ϕ	0.701	0.685	0.729	(0.415, 0.809)
				σ	0.985	>1000	0.739	(0.242, 2.732)
eucalyptus	348.7	6.2	0.039	λ	1.895	1.835	1.711	(0.125, 3.697)
				p	0.327	0.395	0.347	(0.251, 0.866)
				ϕ	0.657	0.584	0.667	(<0.000, 0.794)
				σ	1.625	>1000	1.569	(0.402, 30.464)
Chaco	349.8	7.2	0.023	λ	1.781	1.801	1.697	(0.322, 3.568)
				p	0.344	0.400	0.362	(0.258, 0.724)
				ϕ	0.665	0.617	0.697	(<0.000, 0.805)
				σ	1.475	>1000	1.199	(0.257, 11.809)
Cerrado	349.9	7.3	0.022	λ	1.901	2.158	1.967	(0.58, 4.294)
				p	0.343	0.366	0.346	(0.246, 0.56)
				ϕ	0.675	0.654	0.718	(0.167, 0.813)
				σ	1.506	7.279	1.160	(0.26, 6.393)
Season (wet)	350.9	8.3	0.013	λ	1.695	1.771	1.638	(0.374, 3.537)
				p	0.361	0.431	0.371	(0.265, 0.886)
				ϕ	0.655	0.612	0.675	(<0.000, 0.802)
				σ	1.734	>1000	1.302	(0.369, 10.816)

Agriculture	351.6	9.1	0.009	λ	1.819	1.837	1.823	(0.039, 3.467)
				p	0.322	0.385	0.346	(0.258, 0.83)
				ϕ	0.641	0.585	0.680	(<0.000, 0.804)
				σ	1.789	>1000	1.375	(0.311, 162.469)
Forest	351.7	9.1	0.009	λ	1.938	1.916	1.796	(0.114, 3.997)
				p	0.315	0.401	0.335	(0.244, 0.854)
				ϕ	0.653	0.590	0.699	(<0.000, 0.814)
				σ	1.737	>1000	1.260	(0.281, 30.979)
Sec. vegetation	351.9	9.4	0.008	λ	1.890	2.044	2.042	(0.286, 3.896)
				p	0.317	0.357	0.331	(0.243, 0.631)
				ϕ	0.647	0.617	0.695	(<0.000, 0.798)
				σ	1.808	>1000	1.359	(0.423, 16.099)
Riverine	352.1	9.6	0.007	λ	1.883	2.060	1.915	(0.015, 4.418)
				p	0.318	0.349	0.329	(0.24, 0.521)
				ϕ	0.646	0.578	0.691	(<0.000, 0.809)
				σ	1.834	>1000	1.438	(0.354, 547.746)
River level	352.2	9.7	0.007	λ	1.852	1.909	1.793	(0.142, 3.687)
				p	0.323	0.382	0.347	(0.255, 0.652)
				ϕ	0.646	0.602	0.688	(<0.000, 0.802)
				σ	1.845	>1000	1.420	(0.365, 22.591)
Urban	352.3	9.7	0.007	λ	1.847	1.937	1.907	(0.007, 3.679)
				p	0.320	0.356	0.328	(0.246, 0.598)
				ϕ	0.642	0.576	0.676	(<0.000, 0.802)
				σ	1.867	>1000	1.508	(0.401, 858.936)
Cane	352.3	9.7	0.007	λ	1.852	1.882	1.749	(0.009, 4.143)
				p	0.320	0.358	0.324	(0.25, 0.67)
				ϕ	0.643	0.560	0.650	(<0.000, 0.802)
				σ	1.868	>1000	1.593	(0.416, 1104.432)

Table 3. Population parameter estimates of the single abundance covariate models of *Cathartes* vultures group (*C. aura* and *C. burrovianus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ samples), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Abundance covariates	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Pasture	3422.2	0.0	0.999	λ	3.259	3.413	3.335	(2.78, 4.284)
				p	0.849	0.831	0.843	(0.682, 0.918)
				ϕ	0.045	0.058	0.056	(<0.000, 0.14)
				σ	1.439	1.412	1.396	(1.078, 1.823)
Chaco	3438.8	16.6	0.000	λ	3.061	3.445	3.128	(2.532, 6.237)
				p	0.838	0.790	0.830	(0.402, 0.963)

eucalyptus	3442.3	20.1	0.000	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	1.555	1.585	1.551	(1.235, 2.102)
				λ	3.020	3.303	3.036	(2.477, 5.475)
				p	0.857	0.820	0.853	(0.47, 0.964)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
River level	3444.9	22.7	0.000	σ	1.609	1.613	1.604	(1.21, 2.089)
				λ	3.012	3.361	3.063	(2.539, 5.251)
				p	0.853	0.806	0.851	(0.509, 0.956)
				ϕ	<0.000	0.002	<0.000	(<0.000, <0.000)
Riverine	3451.1	28.9	0.000	σ	1.601	1.606	1.567	(1.222, 2.16)
				λ	2.928	3.220	2.943	(2.451, 4.989)
				p	0.864	0.823	0.857	(0.515, 0.969)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Forest	3451.5	29.3	0.000	σ	1.666	1.664	1.621	(1.272, 2.161)
				λ	2.866	3.138	2.929	(2.403, 4.717)
				p	0.881	0.847	0.882	(0.543, 0.972)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Cerrado	3451.8	29.6	0.000	σ	1.673	1.637	1.605	(1.209, 2.122)
				λ	2.901	3.279	2.977	(2.445, 5.608)
				p	0.872	0.819	0.861	(0.476, 0.967)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Cane	3451.9	29.7	0.000	σ	1.676	1.665	1.645	(1.245, 2.242)
				λ	2.881	3.203	2.961	(2.379, 5.551)
				p	0.881	0.842	0.881	(0.41, 0.97)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Sec. vegetation	3451.9	29.7	0.000	σ	1.677	1.652	1.620	(1.238, 2.172)
				λ	2.907	3.424	2.962	(2.449, 6.735)
				p	0.869	0.801	0.855	(0.381, 0.962)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Urban	3452.0	29.8	0.000	σ	1.675	1.685	1.637	(1.288, 2.312)
				λ	2.897	3.308	2.974	(2.504, 5.865)
				p	0.872	0.816	0.866	(0.413, 0.97)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Season (wet)	3452.1	29.9	0.000	σ	1.675	1.662	1.601	(1.262, 2.245)
				λ	2.944	3.446	3.020	(2.43, 5.972)
				p	0.861	0.793	0.858	(0.382, 0.967)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Agriculture	3452.1	30.0	0.000	σ	1.680	1.706	1.671	(1.233, 2.291)
				λ	2.905	3.306	2.970	(2.38, 6.195)
				p	0.873	0.819	0.870	(0.406, 0.967)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	1.677	1.659	1.622	(1.277, 2.206)

Table 4. Population parameter estimates of the single abundance covariate models of Black Vulture (*Coragyps atratus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated

negative binomial mixture ($n = 1201$ samples), where λ is the rate parameter of the NB distribution, $p =$ detection probability, $\phi =$ zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Pasture	2317.3	0.0	0.998	λ	0.019	0.728	0.187	(<0.000, 2.994)
				p	0.803	0.816	0.821	(0.674, 0.989)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	162.150	(8.253, >1000)
Riverine	2330.1	12.8	0.002	λ	0.198	1.385	0.469	(<0.000, 6.37)
				p	0.339	0.551	0.427	(0.285, 1)
				ϕ	<0.000	0.001	<0.000	(<0.000, <0.000)
				σ	357.727	>1000	115.924	(9.357, >1000)
Cerrado	2334.3	17.0	0.000	λ	0.351	1.037	0.181	(<0.000, 4.483)
				p	0.395	0.567	0.457	(0.253, 0.998)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	155.232	>1000	244.229	(11.086, >1000)
Cane	2338.3	21.0	0.000	λ	0.006	2.146	0.006	(0.006, 0.006)
				p	0.358	0.356	0.358	(0.358, 0.358)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	64.616	0.005	(0.005, 0.005)
Sec. vegetation	2341.5	24.2	0.000	λ	0.001	0.001	0.001	(0.001, 0.001)
				p	0.358	0.360	0.358	(0.358, 0.358)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	542.460	0.001	(0.001, 0.001)
River level	2342.8	25.5	0.000	λ	0.001	0.001	0.001	(0.001, 0.001)
				p	0.368	0.370	0.368	(0.368, 0.368)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	0.001	(0.001, 0.001)
eucalyptus	2345.1	27.7	0.000	λ	0.003	0.201	0.003	(0.003, 0.003)
				p	0.387	0.391	0.387	(0.387, 0.387)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	0.003	(0.003, 0.003)
Forest	2345.3	27.9	0.000	λ	0.014	0.031	0.014	(0.014, 0.022)
				p	0.369	0.378	0.369	(0.369, 0.369)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	0.014	(0.014, 0.014)
Season (wet)	2345.9	28.6	0.000	λ	0.280	1.050	0.242	(<0.000, 4.335)
				p	0.376	0.519	0.436	(0.254, 0.989)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	219.859	>1000	213.748	(14.12, >1000)
Chaco	2346.6	29.3	0.000	λ	0.002	0.040	0.002	(0.002, 0.002)
				p	0.359	0.366	0.359	(0.359, 0.359)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)

Agriculture	2346.8	29.5	0.000	σ	>1000	195.477	0.002	(0.002, 0.002)
				λ	0.017	4.532	0.017	(0.017, 47.526)
				p	0.353	0.377	0.353	(0.168, 0.836)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	0.017	(0.002, 489.573)
Urban	2346.9	29.6	0.000	λ	0.154	1.622	0.298	(<0.000, 7.194)
				p	0.382	0.528	0.407	(0.248, 0.997)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	394.065	>1000	153.643	(7.632, >1000)

Table 5. Population parameter estimates of the single abundance covariate models of Southern Crested-Caracara (*Caracara plancus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ samples), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Abundance covariate	Model Selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Pasture	1468.1	0.0	1000	λ	0.474	0.531	0.502	(<0.000, 1.345)
				p	0.687	0.685	0.696	(0.426, 0.984)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	8.679	>1000	8.406	(2.879, >1000)
Chaco	1485.4	17.2	0.000	λ	<0.000	2.530	1.955	(0.073, 5.569)
				p	0.982	0.879	0.986	(0.225, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, 57.575)
eucalyptus	1489.0	20.8	0.000	λ	<0.000	3.186	2.101	(0.004, 8.92)
				p	0.968	0.791	0.939	(0.178, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, >1000)
Forest	1490.0	21.9	0.000	λ	0.003	8.366	0.308	(<0.000, 2.428)
				p	0.984	0.862	0.982	(0.338, 1)
				ϕ	<0.000	0.009	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	12.354	(<0.000, >1000)
Cane	1493.7	25.6	0.000	λ	0.009	0.137	0.041	(<0.000, 0.494)
				p	0.990	0.967	0.993	(0.887, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	394.260	>1000	94.713	(5.199, >1000)
Riverine	1494.1	26.0	0.000	λ	<0.000	2.373	2.040	(0.08, 2.58)
				p	0.985	0.931	0.991	(0.353, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, 50.107)
River level	1495.3	27.2	0.000	λ	0.001	1.048	0.565	(<0.000, 2.946)

Cerrado	1495.7	27.6	0.000	p	0.985	0.825	0.983	(0.313, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	7.302	(<0.000, >1000)
				λ	0.002	0.732	0.200	(<0.000, 2.334)
				p	0.991	0.887	0.988	(0.341, 1)
				ϕ	<0.000	0.005	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	19.694	(<0.000, >1000)
				λ	0.001	1.394	1.874	(<0.000, 2.283)
Urban	1495.9	27.7	0.000	p	0.994	0.873	0.980	(0.354, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, >1000)
				λ	<0.000	4.697	2.459	(1.882, 19.919)
Season (wet)	1495.9	27.8	0.000	p	0.826	0.740	0.842	(0.105, 0.998)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, <0.000)
				λ	0.001	3.355	2.113	(0.693, 16.167)
Agriculture	1496.0	27.9	0.000	p	0.899	0.851	0.975	(0.13, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, 3.959)
				λ	0.020	0.818	0.004	(<0.000, 2.267)
Sec. vegetation	1496.5	28.4	0.000	p	0.924	0.824	0.956	(0.355, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	188.558	>1000	976.632	(0.01, >1000)
				λ	0.001	1.394	1.874	(<0.000, 2.283)

Table 6. Population parameter estimates of the single abundance covariate models of Savanna Hawk (*Buteogallus meridionalis*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Cerrado	805.4	0.0	0.910	λ	6.659	5.749	6.248	(1.276, 9.765)
				p	0.192	0.333	0.206	(0.124, 0.909)
				ϕ	0.653	0.653	0.654	(0.611, 0.688)
Pasture	810.0	4.6	0.089	λ	8.561	6.518	7.670	(1.31, 10.554)
				p	0.152	0.338	0.163	(0.125, 0.931)
				ϕ	0.653	0.645	0.647	(0.597, 0.681)
Agriculture	819.4	14.0	0.000	λ	8.623	7.235	8.109	(1.268, 10.393)
				p	0.138	0.258	0.144	(0.111, 0.893)
				ϕ	0.626	0.622	0.624	(0.577, 0.665)
Cane	820.6	15.2	0.000	λ	1.293	1.392	1.319	(1.158, 1.749)
				p	0.992	0.947	0.980	(0.781, 0.999)
				ϕ	0.655	0.654	0.657	(0.613, 0.691)

Chaco	826.1	20.7	0.000	λ	8.139	6.373	7.397	(1.354, 10.275)
				p	0.154	0.318	0.167	(0.127, 0.902)
				ϕ	0.652	0.650	0.650	(0.608, 0.689)
Season (wet)	827.8	22.4	0.000	λ	1.326	1.327	1.323	(1.106, 1.528)
				p	0.994	0.993	0.994	(0.982, 1)
				ϕ	0.662	0.660	0.662	(0.616, 0.697)
River level	831.7	26.3	0.000	λ	9.533	7.451	8.801	(1.342, 11.925)
				p	0.137	0.303	0.147	(0.111, 0.907)
				ϕ	0.661	0.655	0.658	(0.616, 0.689)
eucalyptus	834.3	29.0	0.000	λ	10.190	8.914	9.794	(1.501, 12.585)
				p	0.131	0.238	0.136	(0.104, 0.863)
				ϕ	0.665	0.662	0.662	(0.625, 0.702)
Forest	839.1	33.7	0.000	λ	10.609	9.103	10.108	(1.402, 13.279)
				p	0.127	0.245	0.135	(0.099, 0.884)
				ϕ	0.669	0.667	0.669	(0.625, 0.708)
Sec. vegetation	839.3	34.0	0.000	λ	1.336	1.336	1.333	(1.114, 1.547)
				p	0.993	0.994	0.994	(0.992, 0.998)
				ϕ	0.666	0.664	0.662	(0.624, 0.703)
Urban	839.3	34.0	0.000	λ	1.350	1.389	1.356	(1.116, 1.664)
				p	0.994	0.996	0.994	(0.993, 1)
				ϕ	0.668	0.664	0.665	(0.616, 0.698)
Riverine	839.6	34.3	0.000	λ	10.436	8.216	9.607	(1.442, 12.75)
				p	0.128	0.273	0.139	(0.105, 0.892)
				ϕ	0.668	0.662	0.663	(0.621, 0.701)

Table 7. Population parameter estimates of the single abundance covariate models of Roadside Hawk (*Rupornis magnirostris*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Cane	294.4	0.0	0.391	λ	0.533	0.544	0.537	(0.417, 0.691)
				p	0.985	0.962	0.983	(0.863, 0.99)
				ϕ	0.570	0.558	0.565	(0.464, 0.639)
Forest	297.2	2.9	0.094	λ	0.632	1.143	0.656	(0.436, 3.713)
				p	0.800	0.696	0.787	(0.138, 0.988)
				ϕ	0.554	0.546	0.553	(0.417, 0.641)
Riverine	297.5	3.1	0.082	λ	0.554	0.553	0.559	(0.439, 0.664)
				p	0.993	0.993	0.993	(0.992, 0.996)
				ϕ	0.589	0.579	0.589	(0.496, 0.651)
Cerrado	298.0	3.7	0.063	λ	0.566	0.566	0.564	(0.452, 0.672)
				p	0.988	0.988	0.988	(0.988, 0.988)
				ϕ	0.593	0.585	0.589	(0.51, 0.652)

Sec. vegetation	298.1	3.7	0.060	λ	0.551	0.558	0.555	(0.444, 0.681)
				p	0.988	0.987	0.988	(0.986, 0.992)
				ϕ	0.585	0.583	0.587	(0.504, 0.653)
Pasture	298.4	4.0	0.052	λ	0.698	2.134	0.719	(0.506, 8.149)
				p	0.737	0.602	0.717	(0.067, 0.984)
				ϕ	0.562	0.547	0.556	(0.445, 0.636)
Chaco	298.6	4.2	0.048	λ	0.704	1.934	0.723	(0.474, 7.906)
				p	0.707	0.590	0.720	(0.066, 0.957)
				ϕ	0.549	0.535	0.549	(0.403, 0.631)
eucalyptus	298.6	4.2	0.047	λ	0.544	0.578	0.575	(0.432, 0.728)
				p	0.983	0.947	0.982	(0.799, 0.986)
				ϕ	0.580	0.572	0.575	(0.481, 0.641)
Urban	298.7	4.4	0.044	λ	0.551	0.574	0.566	(0.412, 0.727)
				p	0.980	0.947	0.980	(0.799, 0.984)
				ϕ	0.582	0.569	0.576	(0.465, 0.649)
River level	298.8	4.4	0.044	λ	0.713	2.273	0.728	(0.509, 8.192)
				p	0.719	0.587	0.697	(0.061, 0.976)
				ϕ	0.562	0.548	0.554	(0.433, 0.639)
Season (wet)	299.0	4.6	0.039	λ	0.541	0.574	0.566	(0.431, 0.731)
				p	0.987	0.943	0.983	(0.801, 0.994)
				ϕ	0.579	0.571	0.571	(0.486, 0.65)
Agriculture	299.1	4.7	0.037	λ	0.691	2.264	0.720	(0.476, 7.935)
				p	0.721	0.574	0.702	(0.058, 0.962)
				ϕ	0.550	0.533	0.542	(0.393, 0.64)

Table 8. Population parameter estimates of the single abundance covariate models of White-tailed Hawk (*Geranoaetus albicaudatus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Riverine	169.2	0.0	0.149	λ	0.574	0.559	0.558	(0.362, 0.81)
				p	0.994	0.994	0.994	(0.994, 0.994)
				ϕ	0.795	0.779	0.793	(0.689, 0.845)
Urban	169.3	0.1	0.141	λ	8.513	6.872	6.974	(1.105, 9.786)
				p	0.063	0.108	0.075	(0.052, 0.375)
				ϕ	0.778	0.768	0.777	(0.684, 0.828)
Cane	170.0	0.8	0.098	λ	8.116	>1000	6.717	(0.714, 11.19)
				p	0.073	0.133	0.083	(0.055, 0.652)
				ϕ	0.802	0.787	0.792	(0.718, 0.844)
River level	170.2	1.0	0.089	λ	7.062	>1000	6.117	(0.66, 11.482)
				p	0.088	0.180	0.102	(0.06, 0.796)
				ϕ	0.808	0.795	0.801	(0.716, 0.848)

Chaco	170.4	1.2	0.081	λ	8.164	>1000	8.466	(0.729, 13.794)
				p	0.098	0.232	0.125	(0.057, 0.854)
				ϕ	0.823	0.812	0.814	(0.75, 0.863)
Season (wet)	170.4	1.2	0.083	λ	7.955	6.827	7.497	(0.718, 10.699)
				p	0.078	0.174	0.084	(0.054, 0.756)
				ϕ	0.811	0.798	0.803	(0.727, 0.846)
Forest	170.9	1.7	0.063	λ	0.633	>1000	0.654	(0.401, 1.237)
				p	0.994	0.992	0.994	(0.968, 1)
				ϕ	0.813	0.799	0.810	(0.722, 0.85)
Sec. vegetation	170.9	1.7	0.062	λ	9.690	7.061	7.874	(0.653, 11.487)
				p	0.065	0.175	0.081	(0.056, 0.85)
				ϕ	0.811	0.801	0.806	(0.724, 0.85)
Agriculture	171.0	1.8	0.061	λ	8.856	6.825	7.625	(0.543, 11.529)
				p	0.069	0.228	0.081	(0.053, 0.977)
				ϕ	0.808	0.799	0.802	(0.741, 0.851)
Pasture	171.0	1.8	0.061	λ	9.606	7.423	8.833	(0.596, 11.289)
				p	0.065	0.184	0.076	(0.052, 0.883)
				ϕ	0.811	0.796	0.801	(0.705, 0.855)
eucalyptus	171.1	1.9	0.058	λ	9.665	>1000	8.260	(0.583, 11.367)
				p	0.064	0.197	0.076	(0.053, 0.882)
				ϕ	0.809	0.797	0.804	(0.727, 0.849)
Cerrado	171.3	2.1	0.052	λ	9.850	7.323	8.219	(0.625, 11.367)
				p	0.063	0.175	0.075	(0.055, 0.794)
				ϕ	0.810	0.798	0.802	(0.729, 0.853)

Table 9. Population parameter estimates of the single abundance covariate models of American Kestrel (*Falco sparverius*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Season (wet)	312.2	0.0	0.736	λ	1.377	1.867	1.493	(0.93, 5.854)
				p	0.594	0.541	0.552	(0.137, 0.804)
				ϕ	0.729	0.716	0.722	(0.657, 0.759)
eucalyptus	315.8	3.6	0.124	λ	0.953	1.134	1.009	(0.803, 1.461)
				p	0.811	0.755	0.788	(0.547, 0.894)
				ϕ	0.732	0.725	0.725	(0.671, 0.774)
Urban	316.7	4.5	0.078	λ	1.102	1.429	1.126	(0.853, 2.301)
				p	0.730	0.684	0.713	(0.308, 0.86)
				ϕ	0.739	0.730	0.732	(0.677, 0.774)
Agriculture	320.8	8.6	0.010	λ	1.070	1.120	1.113	(0.82, 1.477)
				p	0.733	0.722	0.720	(0.573, 0.864)
				ϕ	0.737	0.731	0.734	(0.68, 0.775)

Pasture	321.1	8.9	0.009	λ	1.057	1.224	1.049	(0.831, 1.478)
				p	0.730	0.704	0.724	(0.525, 0.854)
				ϕ	0.735	0.728	0.730	(0.661, 0.771)
Riverine	321.2	9.0	0.008	λ	1.128	1.297	1.138	(0.921, 1.54)
				p	0.729	0.698	0.697	(0.553, 0.876)
				ϕ	0.746	0.735	0.736	(0.694, 0.775)
River level	321.6	9.4	0.007	λ	1.126	1.480	1.178	(0.89, 1.751)
				p	0.732	0.691	0.699	(0.535, 0.876)
				ϕ	0.747	0.738	0.740	(0.681, 0.783)
Cane	321.7	9.5	0.007	λ	1.130	1.371	1.212	(0.875, 1.782)
				p	0.730	0.698	0.703	(0.529, 0.878)
				ϕ	0.747	0.738	0.740	(0.685, 0.782)
Cerrado	321.8	9.6	0.006	λ	1.094	1.131	1.139	(0.839, 1.388)
				p	0.744	0.733	0.733	(0.574, 0.873)
				ϕ	0.746	0.739	0.739	(0.696, 0.784)
Chaco	321.9	9.7	0.006	λ	1.119	1.313	1.148	(0.885, 1.667)
				p	0.744	0.724	0.740	(0.576, 0.863)
				ϕ	0.749	0.741	0.741	(0.686, 0.789)
Forest	322.1	9.9	0.005	λ	1.105	3.534	1.174	(0.897, 3.041)
				p	0.744	0.695	0.710	(0.461, 0.875)
				ϕ	0.748	0.734	0.737	(0.674, 0.783)
Sec. vegetation	322.1	9.9	0.005	λ	1.106	1.436	1.150	(0.84, 1.838)
				p	0.738	0.688	0.714	(0.478, 0.867)
				ϕ	0.746	0.735	0.737	(0.681, 0.783)

Table 10. Population parameter estimates of the single abundance covariate models of Aplomado Falcon (*Falco femoralis*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Pasture	115.5	0.0	0.540	λ	1.481	1.906	1.235	(0.537, 5.193)
				p	0.427	0.495	0.526	(0.13, 0.858)
				ϕ	0.868	0.846	0.858	(0.75, 0.9)
Riverine	116.5	1.0	0.330	λ	2.953	2.414	2.417	(0.556, 4.692)
				p	0.195	0.382	0.251	(0.13, 0.845)
				ϕ	0.841	0.831	0.832	(0.77, 0.884)
Cerrado	118.4	2.8	0.130	λ	4.138	2.729	2.696	(0.659, 5.085)
				p	0.155	0.320	0.187	(0.139, 0.834)
				ϕ	0.884	0.867	0.877	(0.79, 0.921)
Chaco	128.8	13.2	0.000	λ	5.834	5.105	4.842	(1.178, 11.33)
				p	0.178	0.305	0.202	(0.104, 0.828)
				ϕ	0.917	0.912	0.913	(0.889, 0.933)

Forest	129.1	13.6	0.000	λ	2.524	3.631	2.440	(0.994, 10.361)
				p	0.399	0.440	0.417	(0.096, 0.831)
				ϕ	0.915	0.909	0.912	(0.878, 0.931)
Urban	131.1	15.5	0.000	λ	2.213	3.795	1.744	(0.889, 10.402)
				p	0.439	0.504	0.547	(0.094, 0.934)
				ϕ	0.912	0.910	0.911	(0.888, 0.931)
Sec. vegetation	131.5	16.0	0.000	λ	2.490	18.022	2.033	(0.897, 12.089)
				p	0.434	0.501	0.558	(0.097, 0.898)
				ϕ	0.921	0.917	0.918	(0.891, 0.938)
Cane	131.6	16.1	0.000	λ	2.707	>1000	2.642	(1.005, 12.206)
				p	0.391	0.438	0.404	(0.1, 0.871)
				ϕ	0.921	0.916	0.918	(0.889, 0.937)
eucalyptus	132.2	16.6	0.000	λ	2.056	4.072	1.691	(0.771, 11.214)
				p	0.489	0.522	0.577	(0.093, 0.938)
				ϕ	0.915	0.912	0.913	(0.889, 0.934)
River level	132.7	17.2	0.000	λ	2.155	>1000	2.841	(1.058, >1000)
				p	0.533	0.502	0.570	(0.1, 0.897)
				ϕ	0.925	0.921	0.922	(0.897, 0.941)
Agriculture	132.9	17.4	0.000	λ	2.422	5.044	2.376	(0.959, 12.065)
				p	0.467	0.476	0.527	(0.086, 0.909)
				ϕ	0.925	0.920	0.922	(0.895, 0.938)
Season (wet)	132.9	17.4	0.000	λ	2.840	4.895	2.553	(0.881, 11.838)
				p	0.399	0.464	0.444	(0.095, 0.938)
				ϕ	0.924	0.919	0.920	(0.897, 0.943)

Table 11. Population parameter estimates of the single abundance covariate models of Snail Kite (*Rothramus sociabilis*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 195$ samples), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
River level	166.1	0.0	0.982	λ	1.611	1.720	1.552	(<0.000, 3.675)
				p	0.481	0.579	0.553	(0.373, 0.847)
				ϕ	<0.000	0.007	<0.000	(<0.000, <0.000)
				σ	3.178	>1000	1.965	(0.122, >1000)
Agriculture	175.6	9.6	0.008	λ	0.006	0.807	0.464	(<0.000, 2.719)
				p	0.783	0.770	0.787	(0.518, 0.876)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	682.129	>1000	7.249	(<0.000, >1000)
Riverine	177.4	11.3	0.003	λ	0.016	0.330	0.001	(<0.000, 1.572)
				p	0.757	0.736	0.781	(0.41, 0.867)

Pasture	178.8	12.7	0.002	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	293.791	>1000	>1000	(1.438, >1000)
				λ	0.005	0.307	0.003	(<0.000, 1.902)
				p	0.937	0.836	0.874	(0.567, 1)
				ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	682.083	>1000	>1000	(<0.000, >1000)
				λ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				p	0.714	0.714	0.714	(0.714, 0.714)
Urban	179.5	13.4	0.001	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, <0.000)
				λ	0.018	0.355	0.002	(<0.000, 1.666)
				p	0.794	0.775	0.790	(0.448, 0.925)
Cerrado	179.9	13.8	0.001	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	225.628	>1000	>1000	(0.792, >1000)
				λ	<0.000	1.990	2.145	(<0.000, 3.19)
				p	0.789	0.807	0.801	(0.754, 0.87)
Sec. vegetation	180.0	13.9	0.000	ϕ	<0.000	0.006	<0.000	(<0.000, <0.000)
				σ	>1000	>1000	<0.000	(<0.000, >1000)
				λ	0.005	0.907	0.521	(<0.000, 2.676)
				p	0.784	0.784	0.789	(0.674, 0.89)
Chaco	180.2	14.1	0.000	ϕ	<0.000	0.012	<0.000	(<0.000, <0.000)
				σ	860.481	>1000	7.098	(<0.000, >1000)
				λ	0.003	0.601	0.067	(<0.000, 2.506)
				p	0.794	0.807	0.800	(0.662, 0.974)
Season (wet)	180.8	14.7	0.000	ϕ	<0.000	0.123	<0.000	(<0.000, 0.628)
				σ	>1000	>1000	67.611	(<0.000, >1000)
				λ	0.010	182.111	0.001	(<0.000, 4.02)
				p	0.793	0.806	0.800	(0.674, 0.931)
Forest	181.0	14.9	0.000	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
				σ	511.507	>1000	>1000	(1.653, >1000)

Table 12. Population parameter estimates of the single abundance covariate models of Black-collared Hawk (*Busarellus nigricolis*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated Poisson mixture ($n = 195$ samples), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Forest	114.0	0.0	0.562	λ	1.157	1.128	1.157	(0.753, 1.488)
				p	0.801	0.807	0.806	(0.774, 0.831)
				ϕ	0.544	0.527	0.538	(0.381, 0.644)
Cerrado	116.4	2.5	0.165	λ	1.350	1.275	1.286	(0.835, 1.706)
				p	0.949	0.951	0.949	(0.949, 0.964)

River level	118.3	4.3	0.065	ϕ	0.663	0.641	0.645	(0.52, 0.733)
				λ	1.379	1.410	1.405	(0.91, 1.934)
				p	0.941	0.907	0.933	(0.768, 0.954)
Pasture	118.3	4.4	0.063	ϕ	0.662	0.636	0.641	(0.539, 0.728)
				λ	1.145	1.119	1.131	(0.618, 1.656)
				p	0.942	0.930	0.939	(0.877, 0.944)
Riverine	119.4	5.4	0.038	ϕ	0.613	0.575	0.593	(0.387, 0.736)
				λ	1.331	1.468	1.414	(0.948, 2.014)
				p	0.925	0.897	0.911	(0.815, 0.944)
Chaco	119.6	5.6	0.034	ϕ	0.655	0.639	0.646	(0.54, 0.727)
				λ	1.507	1.446	1.468	(0.972, 1.927)
				p	0.933	0.940	0.939	(0.933, 0.954)
Season (wet)	119.7	5.8	0.031	ϕ	0.681	0.671	0.677	(0.569, 0.756)
				λ	2.322	3.809	2.575	(1.143, 10.022)
				p	0.616	0.572	0.603	(0.133, 0.943)
Sec. vegetation	120.2	6.2	0.025	ϕ	0.673	0.654	0.660	(0.544, 0.733)
				λ	1.301	>1000	1.301	(0.815, 1.625)
				p	0.940	0.923	0.938	(0.856, 0.95)
Agriculture	122.3	8.3	0.009	ϕ	0.646	0.627	0.632	(0.519, 0.709)
				λ	1.354	23.699	1.485	(1, 3.094)
				p	0.939	0.906	0.923	(0.825, 0.954)
Urban	122.3	8.3	0.009	ϕ	0.668	0.651	0.658	(0.552, 0.737)
				λ	>1000	>1000	>1000	(1.13, >1000)
				p	0.940	0.890	0.917	(0.743, 0.957)
				ϕ	0.677	0.661	0.667	(0.543, 0.746)

Table 13. Population parameter estimates of the single abundance covariate models of Great Black Hawk (*Urubitinga urubitinga*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated Poisson mixture ($n = 195$ samples), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariate	Model selection			Parameter	Estimate mean	Bootstrap		
	AICc	dAICc	Weight			Mean	Median	90% CI
Riverine	111.3	0.0	0.335	λ	1.390	1.505	1.421	(1.074, 2.124)
				p	0.728	0.711	0.699	(0.483, 0.939)
				ϕ	0.507	0.492	0.487	(0.382, 0.605)
Sec. vegetation	111.9	0.6	0.253	λ	3.475	193.270	4.442	(1.413, 9.445)
				p	0.637	0.620	0.638	(0.418, 0.768)
				ϕ	0.540	0.537	0.534	(0.428, 0.639)
Agriculture	112.8	1.5	0.157	λ	1.096	>1000	1.124	(0.805, 3.581)
				p	0.773	0.722	0.763	(0.230, 0.944)
				ϕ	0.460	0.451	0.461	(0.320, 0.563)
Cerrado	114.6	3.3	0.065	λ	1.139	1.364	1.210	(0.853, 1.879)

				p	0.798	0.756	0.777	(0.454,0.949)
				ϕ	0.502	0.496	0.503	(0.363,0.619)
				λ	1.505	2.111	1.561	(1.080,6.804)
Season (wet)	115.7	4.4	0.038	p	0.672	0.619	0.650	(0.135,0.921)
				ϕ	0.527	0.517	0.521	(0.419,0.611)
				λ	1.280	2.015	1.354	(0.921,6.894)
Forest	115.8	4.5	0.036	p	0.702	0.609	0.658	(0.120,0.935)
				ϕ	0.492	0.477	0.485	(0.359,0.585)
				λ	1.290	>1000	1.290	(0.963,2.071)
Urban	115.8	4.5	0.035	p	0.731	0.712	0.731	(0.430,0.901)
				ϕ	0.515	0.496	0.506	(0.380,0.598)
				λ	1.395	1.910	1.443	(1.053,6.853)
Chaco	116.0	4.7	0.033	p	0.736	0.686	0.725	(0.146,0.941)
				ϕ	0.544	0.540	0.535	(0.436,0.653)
				λ	1.543	2.093	1.642	(1.18,5.855)
River level	116.1	4.8	0.030	p	0.701	0.636	0.674	(0.174,0.907)
				ϕ	0.552	0.533	0.544	(0.413,0.628)
				λ	1.342	1.716	1.293	(0.776,4.733)
Pasture	117.1	5.8	0.019	p	0.721	0.666	0.704	(0.145,0.939)
				ϕ	0.524	0.464	0.480	(0.253,0.635)

Appendix D

Table 1. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of *Cathartes* vultures (*C. aura* and *C. burrovianus*). Rescaled AICc weights are given for models within 0,95 cumulative weight. All models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	3413.5	0.0	0.075	0.075	0.079
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, river level	3413.6	0.2	0.069	0.144	0.073
Cerrado, forest, agriculture, pasture, eucalyptus, sec. vegetation, river level	3413.6	0.2	0.069	0.213	0.073
Cerrado, forest, agriculture, pasture, eucalyptus, river level	3413.7	0.2	0.068	0.281	0.072
Cerrado, agriculture, pasture, eucalyptus, river level	3413.7	0.2	0.066	0.347	0.069
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3413.9	0.4	0.061	0.408	0.064
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, river level	3414.4	0.9	0.048	0.456	0.051
Cerrado, forest, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3414.5	1.0	0.046	0.502	0.048
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, river level	3414.9	1.4	0.037	0.539	0.039
Cerrado, riverine, agriculture, pasture, eucalyptus, river level	3415.0	1.5	0.035	0.574	0.037
Cerrado, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	3415.2	1.7	0.031	0.605	0.033
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3415.4	2.0	0.028	0.633	0.029
Riverine, agriculture, pasture, eucalyptus, river level	3415.6	2.1	0.026	0.659	0.027
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3415.7	2.3	0.024	0.683	0.025
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	3415.7	2.3	0.024	0.707	0.025
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level	3416.0	2.5	0.022	0.729	0.023
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	3416.0	2.5	0.021	0.750	0.022
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3416.0	2.5	0.021	0.771	0.022
Cerrado, forest, riverine, agriculture, pasture, eucalyptus	3416.6	3.1	0.016	0.787	0.017
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	3416.6	3.2	0.015	0.802	0.016
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	3416.8	3.3	0.014	0.816	0.015
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation	3416.9	3.4	0.013	0.829	0.014

Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	3417.0	3.5	0.013	0.842	0.014
Forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	3417.1	3.7	0.012	0.854	0.013
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	3417.5	4.0	0.010	0.864	0.011
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level	3417.6	4.1	0.009	0.873	0.009
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	3417.6	4.1	0.009	0.882	0.009
Forest, riverine, agriculture, pasture, eucalyptus, river level	3417.8	4.3	0.009	0.891	0.009
Cerrado, riverine, pasture, eucalyptus, river level	3417.8	4.4	0.008	0.899	0.008
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3417.8	4.4	0.008	0.907	0.008
Cerrado, riverine, agriculture, pasture, eucalyptus	3417.9	4.4	0.008	0.915	0.008
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3417.9	4.5	0.008	0.923	0.008
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	3418.1	4.6	0.007	0.930	0.007
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	3418.1	4.7	0.007	0.937	0.007
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	3418.3	4.8	0.007	0.944	0.007
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	3418.3	4.8	0.007	0.951	
Cerrado, forest, riverine, pasture, eucalyptus, river level	3418.4	4.9	0.006	0.957	
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	3419.0	5.5	0.005	0.962	
Cerrado, forest, riverine, pasture, eucalyptus, sec. vegetation, river level	3419.2	5.8	0.004	0.966	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	3419.3	5.8	0.004	0.970	
Cerrado, forest, riverine, agriculture, pasture, river level	3419.5	6.0	0.004	0.974	
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	3419.5	6.1	0.004	0.978	
Cerrado, forest, riverine, pasture, eucalyptus, cane, sec. vegetation, river level	3419.8	6.3	0.003	0.981	
Cerrado, riverine, agriculture, pasture, river level	3419.9	6.4	0.003	0.984	
Cerrado, forest, riverine, agriculture, pasture, sec. vegetation, river level	3419.9	6.4	0.003	0.987	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	3420.3	6.8	0.002	0.989	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	3420.3	6.9	0.002	0.991	
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	3421.2	7.7	0.002	0.993	
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, river level	3421.4	7.9	0.001	0.994	
Cerrado, forest, riverine, agriculture, pasture, cane, sec. vegetation, river level	3421.7	8.2	0.001	0.995	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	3422.6	9.2	0.001	0.996	
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, river level	3423.3	9.8	0.001	0.997	

Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level	3423.3	9.9	0.001	0.998
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	3423.4	9.9	0.001	0.999
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level	3425.0	11.5	<0.001	>0.999
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	3425.6	12.2	<0.001	>0.999
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	3425.8	12.4	<0.001	>0.999
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level	3435.3	21.8	<0.001	>0.999
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level	3436.6	23.1	<0.001	>0.999
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	3438.5	25.0	<0.001	>0.999
Cerrado, riverine, agriculture, eucalyptus, river level	3442.1	28.6	<0.001	>0.999
Cerrado, forest, riverine, agriculture, eucalyptus, river level	3444.0	30.5	<0.001	>0.999
Cerrado, forest, riverine, agriculture, eucalyptus, sec. vegetation, river level	3446.5	33.0	<0.001	>0.999
Cerrado, forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level	3449.6	36.1	<0.001	>0.999

Table 2. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Black Vultures (*Coragyps atratus*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Riverine, pasture, cane, sec. vegetation, season (wet)	2295	0	0.198	0.198	0.209
Riverine, pasture, cane, sec. vegetation, urban, season (wet)	2295.7	0.7	0.138	0.335	0.146
Riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2296.2	1.2	0.108	0.443	0.114
Riverine, pasture, eucalyptus, cane, sec. vegetation, season (wet)	2296.6	1.6	0.087	0.530	0.092
Forest, riverine, pasture, eucalyptus, cane, sec. vegetation, season (wet)	2298	3	0.044	0.574	0.047
Forest, riverine, pasture, cane, sec. vegetation, urban, season (wet)	2298	3	0.043	0.618	0.046
Cerrado, forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2298.5	3.5	0.034	0.652	0.036
Forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2298.5	3.6	0.033	0.685	0.035
Riverine, pasture, cane, sec. vegetation	2298.7	3.8	0.030	0.715	0.032
Cerrado, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2299.2	4.2	0.024	0.739	0.026

Cerrado, forest, riverine, pasture, eucalyptus, cane, sec. vegetation, season (wet)	2299.6	4.7	0.019	0.758	0.020
Riverine, pasture, cane, sec. vegetation, urban	2299.7	4.7	0.019	0.777	0.020
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2299.8	4.9	0.018	0.795	0.019
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet)	2299.8	4.9	0.017	0.812	0.018
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2300.1	5.2	0.015	0.827	0.016
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet)	2300.2	5.2	0.015	0.842	0.016
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2300.3	5.4	0.014	0.855	0.014
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2300.4	5.4	0.013	0.868	0.014
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2300.4	5.5	0.013	0.881	0.014
Cerrado, forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban	2300.8	5.8	0.011	0.892	0.011
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, season (wet)	2300.8	5.9	0.011	0.903	0.011
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2301	6	0.010	0.912	0.010
Riverine, pasture, sec. vegetation, urban, season (wet)	2301	6.1	0.010	0.922	0.010
Riverine, pasture, eucalyptus, cane, sec. vegetation, urban	2301.3	6.3	0.009	0.930	0.009
Cerrado, forest, riverine, agriculture, pasture, cane, sec. vegetation, urban, season (wet)	2301.6	6.7	0.007	0.937	0.008
Riverine, pasture, sec. vegetation, season (wet)	2301.8	6.8	0.007	0.944	0.007
Forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban	2301.9	6.9	0.006	0.951	
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	2302.1	7.1	0.006	0.956	
Riverine, pasture, eucalyptus, sec. vegetation, urban, season (wet)	2302.3	7.3	0.005	0.961	
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2302.4	7.5	0.005	0.966	
Riverine, pasture, cane, season (wet)	2302.6	7.6	0.004	0.970	
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	2302.7	7.7	0.004	0.974	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	2302.8	7.8	0.004	0.978	
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	2302.8	7.8	0.004	0.982	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	2303	8	0.004	0.986	
Cerrado, forest, riverine, pasture, cane, sec. vegetation, urban, season (wet)	2303.4	8.4	0.003	0.989	
Forest, riverine, pasture, eucalyptus, sec. vegetation, urban, season (wet)	2303.6	8.7	0.003	0.991	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	2305.1	10.2	0.001	0.992	
Pasture, cane, sec. vegetation, season (wet)	2305.5	10.6	<0.001	>0.992	
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	2305.6	10.7	<0.001	>0.992	

Cerrado, forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, season (wet)	2305.7	10.8	<0.001	>0.992
Riverine, pasture, eucalyptus, cane, urban, season (wet)	2306.2	11.2	<0.001	>0.992
Forest, riverine, pasture, eucalyptus, cane, urban, season (wet)	2306.6	11.7	<0.001	>0.992
Pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2306.9	11.9	<0.001	>0.992
Riverine, pasture, cane, urban, season (wet)	2307	12.1	<0.001	>0.992
Cerrado, forest, riverine, pasture, eucalyptus, sec. vegetation, urban, season (wet)	2307.4	12.4	<0.001	>0.992
Pasture, cane, sec. vegetation, urban, season (wet)	2307.4	12.4	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, season (wet)	2307.5	12.6	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	2307.8	12.9	<0.001	>0.992
Cerrado, forest, riverine, pasture, eucalyptus, cane, urban, season (wet)	2308.4	13.4	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	2308.7	13.7	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	2309	14	<0.001	>0.992
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2310.7	15.7	<0.001	>0.992
Cerrado, forest, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2310.9	15.9	<0.001	>0.992
Forest, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2310.9	15.9	<0.001	>0.992
Cerrado, forest, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2311.7	16.7	<0.001	>0.992
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, urban, season (wet)	2312.2	17.3	<0.001	>0.992
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	2312.9	17.9	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, season (wet)	2313.2	18.3	<0.001	>0.992
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	2313.9	19	<0.001	>0.992
Cerrado, forest, riverine, eucalyptus, cane, sec. vegetation, urban, season (wet)	2314.3	19.3	<0.001	>0.992
Cerrado, forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2315.6	20.7	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	2315.9	20.9	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, season (wet)	2316.7	21.7	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	2317.2	22.3	<0.001	>0.992
Riverine, cane, sec. vegetation, season (wet)	2321.9	27	<0.001	>0.992
Riverine, eucalyptus, cane, sec. vegetation, urban, season (wet)	2323.7	28.8	<0.001	>0.992
Riverine, cane, sec. vegetation, urban, season (wet)	2324.1	29.1	<0.001	>0.992
Forest, riverine, eucalyptus, cane, sec. vegetation, urban, season (wet)	2325.5	30.5	<0.001	>0.992

Table 3. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Southern Crested-Caracara (*Caracara plancus*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Cerrado, pasture, eucalyptus, cane	1462.5	0	0.106	0.106	0.112
Cerrado, agriculture, pasture, eucalyptus, cane	1462.7	0.2	0.097	0.203	0.102
Cerrado, riverine, agriculture, pasture, eucalyptus, cane	1463.3	0.8	0.072	0.275	0.076
Cerrado, chaco, agriculture, pasture, eucalyptus, cane	1463.9	1.4	0.053	0.328	0.056
Cerrado, riverine, pasture, eucalyptus, cane	1464	1.5	0.051	0.378	0.054
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane	1464	1.5	0.050	0.429	0.053
Cerrado, pasture, cane	1464.3	1.8	0.043	0.472	0.046
Cerrado, agriculture, pasture, cane	1464.6	2	0.039	0.511	0.041
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, river level	1464.6	2.1	0.038	0.549	0.040
Cerrado, chaco, agriculture, pasture, eucalyptus, cane, river level	1464.7	2.2	0.036	0.585	0.038
Cerrado, pasture, eucalyptus	1464.8	2.2	0.035	0.620	0.037
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, river level	1465	2.5	0.031	0.651	0.033
Cerrado, riverine, agriculture, pasture, cane	1465.1	2.6	0.030	0.681	0.031
Cerrado, agriculture, pasture, eucalyptus	1465.1	2.6	0.030	0.710	0.031
Pasture, eucalyptus, cane	1465.3	2.7	0.027	0.737	0.029
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1465.9	3.3	0.020	0.758	0.021
Cerrado, riverine, agriculture, pasture, eucalyptus	1466.1	3.6	0.018	0.776	0.019
Cerrado, chaco, riverine, agriculture, pasture, cane	1466.2	3.6	0.017	0.793	0.018
Cerrado, pasture	1466.4	3.8	0.016	0.809	0.017
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	1466.6	4	0.014	0.823	0.015
Cerrado, chaco, riverine, pasture, eucalyptus, cane	1466.6	4	0.014	0.837	0.015
Agriculture, pasture, eucalyptus, cane	1466.7	4.2	0.013	0.850	0.014
Cerrado, chaco, riverine, agriculture, pasture, cane, river level	1466.9	4.3	0.012	0.863	0.013
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1467	4.5	0.011	0.874	0.012

Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, river level	1467.1	4.5	0.011	0.885	0.012
Pasture, cane	1467.1	4.5	0.011	0.896	0.012
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus	1467.6	5.1	0.009	0.905	0.009
Riverine, agriculture, pasture, eucalyptus, cane	1467.6	5.1	0.009	0.913	0.009
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	1467.7	5.2	0.008	0.921	0.008
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1468.0	5.4	0.007	0.928	0.007
Cerrado, chaco, riverine, pasture, eucalyptus, cane, river level	1468.2	5.7	0.006	0.934	0.007
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1468.4	5.8	0.006	0.940	0.006
Cerrado, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1468.7	6.2	0.005	0.945	0.005
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1468.8	6.2	0.005	0.950	0.005
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet)	1468.9	6.3	0.005	0.954	
Cerrado, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, river level	1468.9	6.3	0.005	0.959	
Cerrado, chaco, riverine, agriculture, pasture, cane, sec. vegetation, river level	1469.2	6.7	0.004	0.962	
Chaco, riverine, agriculture, pasture, eucalyptus, cane	1469.3	6.7	0.004	0.966	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	1469.3	6.7	0.004	0.970	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, river level	1469.5	7	0.003	0.973	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	1469.8	7.3	0.003	0.976	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, river level, season (wet)	1470.2	7.7	0.002	0.978	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	1470.4	7.8	0.002	0.980	
Chaco, riverine, agriculture, pasture, eucalyptus, cane, river level	1470.8	8.2	0.002	0.982	
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	1470.8	8.2	0.002	0.984	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	1470.9	8.3	0.002	0.985	
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, river level	1470.9	8.3	0.002	0.987	
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	1471	8.4	0.002	0.989	
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	1471	8.4	0.002	0.990	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	1471	8.5	0.002	0.992	
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, river level	1471.5	9	0.001	0.993	
Chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1471.9	9.3	<0.001	>0.993	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	1471.9	9.4	<0.001	>0.993	
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	1472.2	9.7	<0.001	>0.993	

Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	1472.6	0.1	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	1472.7	0.1	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, river level, season (wet)	1473.4	0.9	<0.001	>0.993
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	1473.4	0.9	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	1473.8	1.2	<0.001	>0.993
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	1473.8	1.2	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	1474.1	1.6	<0.001	>0.993
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	1474.3	1.8	<0.001	>0.993
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	1475	2.5	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level, season (wet)	1475.1	2.5	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	1475.4	2.9	<0.001	>0.993
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	1476.5	4	<0.001	>0.993
Cerrado, chaco, riverine, agriculture, eucalyptus, cane	1485.6	3	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level, season (wet)	1486.8	4.3	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level	1487.5	5	<0.001	>0.993
Cerrado, chaco, riverine, agriculture, eucalyptus, cane, river level	1487.7	5.1	<0.001	>0.993
Cerrado, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level	1488.8	6.3	<0.001	>0.993
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	1488.9	6.4	<0.001	>0.993
Cerrado, eucalyptus, cane	1491.5	9	<0.001	>0.993
Cerrado, agriculture, eucalyptus, cane	1492.6	0	<0.001	>0.993
Cerrado, riverine, agriculture, eucalyptus, cane	1494.9	2.4	<0.001	>0.993
Cerrado, cane	1497.2	4.7	<0.001	>0.993

Table 4. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Savanna Hawk (*Buteogallus meridionalis*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	747.5	0	0.167	0.167	0.177

Cerrado, chaco, riverine, agriculture, urban, cane, sec. vegetation, river level, season (wet)	748.7	1.2	0.092	0.259	0.097
Cerrado, chaco, agriculture, urban, cane, river level, season (wet)	748.9	1.4	0.082	0.340	0.086
Cerrado, chaco, riverine, agriculture, urban, eucalyptus, cane, river level, season (wet)	749.2	1.7	0.071	0.411	0.075
Cerrado, chaco, riverine, agriculture, urban, cane, river level, season (wet)	749.3	1.8	0.069	0.480	0.073
Cerrado, chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	749.5	2	0.061	0.541	0.065
Cerrado, chaco, urban, cane, river level, season (wet)	750.3	2.7	0.043	0.584	0.045
Cerrado, chaco, riverine, urban, cane, river level, season (wet)	750.3	2.7	0.042	0.626	0.045
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	750.3	2.8	0.041	0.668	0.044
Cerrado, chaco, riverine, urban, cane, sec. vegetation, river level, season (wet)	750.7	3.2	0.034	0.701	0.036
Cerrado, chaco, agriculture, urban, cane, sec. vegetation, river level, season (wet)	750.8	3.3	0.032	0.733	0.034
Cerrado, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level, season (wet)	750.9	3.4	0.031	0.764	0.033
Cerrado, chaco, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	750.9	3.4	0.030	0.795	0.032
Cerrado, chaco, riverine, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	751.3	3.7	0.026	0.820	0.027
Cerrado, chaco, riverine, agriculture, cane, river level, season (wet)	751.4	3.9	0.024	0.844	0.025
Cerrado, chaco, riverine, agriculture, cane, sec. vegetation, river level, season (wet)	751.9	4.4	0.018	0.863	0.019
Cerrado, chaco, agriculture, cane, river level, season (wet)	752.1	4.5	0.017	0.880	0.018
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	752.1	4.6	0.017	0.897	0.018
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	752.6	5.1	0.013	0.910	0.014
Cerrado, forest, chaco, riverine, agriculture, urban, cane, sec. vegetation, river level, season (wet)	752.7	5.2	0.013	0.923	0.013
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	752.8	5.3	0.012	0.934	0.013
Cerrado, chaco, riverine, agriculture, urban, sec. vegetation, river level, season (wet)	753.3	5.8	0.009	0.944	0.010
Cerrado, chaco, cane, river level, season (wet)	753.5	5.9	0.009	0.952	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	753.5	5.9	0.009	0.961	
Cerrado, chaco, riverine, agriculture, urban, eucalyptus, sec. vegetation, river level, season (wet)	753.6	6.1	0.008	0.969	
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	753.7	6.2	0.008	0.976	
Cerrado, chaco, riverine, agriculture, urban, river level, season (wet)	754.5	7	0.005	0.981	
Cerrado, forest, chaco, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	755.4	7.9	0.003	0.985	
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level, season (wet)	755.5	8	0.003	0.988	
Cerrado, chaco, agriculture, urban, river level, season (wet)	755.5	8	0.003	0.991	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	756.1	8.6	0.002	0.993	

Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	756.6	9.1	0.002	0.995
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	756.9	9.4	0.002	0.997
Cerrado, chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, season (wet)	758.5	11	<0.001	>0.997
Cerrado, chaco, riverine, agriculture, urban, cane, sec. vegetation, season (wet)	758.6	11	<0.001	>0.997
Cerrado, chaco, urban, river level, season (wet)	758.6	11.1	<0.001	>0.997
Cerrado, chaco, riverine, agriculture, urban, cane, season (wet)	759.8	12.2	<0.001	>0.997
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	759.8	12.3	<0.001	>0.997
Cerrado, chaco, agriculture, urban, cane, season (wet)	760	12.5	<0.001	>0.997
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	762.2	14.6	<0.001	>0.997
Cerrado, chaco, riverine, agriculture, urban, cane, sec. vegetation, river level	763	15.5	<0.001	>0.997
Cerrado, forest, chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, season (wet)	763.3	15.8	<0.001	>0.997
Cerrado, chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level	763.3	15.8	<0.001	>0.997
Cerrado, chaco, urban, cane, season (wet)	763.5	16	<0.001	>0.997
Cerrado, chaco, riverine, agriculture, urban, cane, river level	764.2	16.7	<0.001	>0.997
Cerrado, chaco, urban, agriculture, cane, river level	764.9	17.4	<0.001	>0.997
Cerrado, agriculture, urban, cane, river level, season (wet)	765.5	18	<0.001	>0.997
Cerrado, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	765.8	18.3	<0.001	>0.997
Cerrado, forest, chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level	766.7	19.2	<0.001	>0.997
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	767	19.5	<0.001	>0.997
Cerrado, riverine, agriculture, urban, cane, river level, season (wet)	767.2	19.7	<0.001	>0.997
Cerrado, chaco, urban, cane, river level	768	20.4	<0.001	>0.997
Cerrado, forest, chaco, riverine, agriculture, urban, eucalyptus, sec. vegetation, river level, season (wet)	768.5	20.9	<0.001	>0.997
Cerrado, riverine, agriculture, urban, cane, sec. vegetation, river level, season (wet)	769	21.5	<0.001	>0.997
Cerrado, forest, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	769.2	21.7	<0.001	>0.997
Cerrado, urban, cane, river level, season (wet)	769.4	21.9	<0.001	>0.997
Cerrado, forest, chaco, riverine, agriculture, urban, eucalyptus, cane, river level, season (wet)	773	25.5	<0.001	>0.997
Chaco, agriculture, urban, cane, river level, season (wet)	784	36.5	<0.001	>0.997
Forest, chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	784.8	37.3	<0.001	>0.997
Chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	785.1	37.6	<0.001	>0.997
Chaco, riverine, agriculture, urban, cane, river level, season (wet)	786.5	39	<0.001	>0.997

Chaco, riverine, agriculture, urban, cane, sec. vegetation, river level, season (wet)	788.6	41.1	<0.001	>0.997
Chaco, urban, cane, river level, season (wet)	790.4	42.9	<0.001	>0.997
Cerrado, forest, chaco, riverine, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	803.5	56	<0.001	>0.997

Table 5. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Roadside Hawk (*Rupornis magnirostris*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Cane	294.1	0	0.202	0.202	0.213
Riverine, cane	295.2	1.1	0.119	0.321	0.125
Riverine, cane, sec. vegetation	295.5	1.3	0.105	0.426	0.110
Riverine, pasture, cane	295.7	1.5	0.094	0.519	0.099
Cane, sec. vegetation	296.2	2	0.074	0.593	0.078
Riverine, pasture, cane, sec. vegetation	297.2	3	0.045	0.638	0.047
Pasture, cane, sec. vegetation	297.2	3	0.044	0.682	0.046
Cerrado, riverine, pasture, cane	297.3	3.1	0.042	0.724	0.045
Cerrado, pasture, cane, sec. vegetation	297.4	3.3	0.039	0.763	0.041
Riverine	297.5	3.4	0.038	0.801	0.040
Cerrado, riverine, cane, sec. vegetation	297.9	3.8	0.031	0.832	0.033
Cerrado, riverine, pasture, cane, sec. vegetation	298.6	4.5	0.021	0.853	0.022
Riverine, sec. vegetation	298.7	4.6	0.021	0.874	0.022
Cerrado, chaco, riverine, cane, sec. vegetation	299.6	5.5	0.013	0.887	0.014
Cerrado, chaco, riverine, pasture, cane	300.1	6	0.010	0.897	0.011
Riverine, pasture, sec. vegetation	300.1	6	0.010	0.907	0.011
Cerrado, chaco, riverine, pasture, cane, sec. vegetation	300.2	6	0.010	0.917	0.010
Chaco, riverine, pasture, cane, sec. vegetation	300.5	6.4	0.008	0.925	0.009
Cerrado, chaco, riverine, agriculture, pasture, cane	300.7	6.5	0.008	0.933	0.008
Cerrado, riverine, agriculture, pasture, cane, sec. vegetation	300.7	6.6	0.008	0.941	0.008

Cerrado, chaco, pasture, cane, sec. vegetation	300.8	6.6	0.007	0.948	0.008
Cerrado, riverine, pasture, sec. vegetation	301.5	7.4	0.005	0.953	
Cerrado, chaco, riverine, agriculture, pasture, cane, sec. vegetation	301.6	7.5	0.005	0.958	
Cerrado, chaco, agriculture, pasture, cane, sec. vegetation	301.6	7.5	0.005	0.962	
Chaco, riverine, agriculture, pasture, cane, sec. vegetation	301.9	7.8	0.004	0.967	
Cerrado, chaco, riverine, agriculture, cane, sec. vegetation	302.6	8.4	0.003	0.970	
Cerrado, chaco, agriculture, pasture, cane, sec. vegetation, urban	302.6	8.5	0.003	0.972	
Cerrado, chaco, riverine, pasture, cane, sec. vegetation, urban	303	8.9	0.002	0.975	
Cerrado, chaco, riverine, agriculture, pasture, cane, urban	303.1	8.9	0.002	0.977	
Cerrado, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban	303.5	9.3	0.002	0.979	
Cerrado, chaco, riverine, pasture, sec. vegetation	303.6	9.4	0.002	0.981	
Cerrado, riverine, agriculture, pasture, cane, sec. vegetation, urban	303.6	9.5	0.002	0.983	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	303.6	9.5	0.002	0.984	
Chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban	304	9.8	0.002	0.986	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban	304.3	0.2	0.001	0.987	
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation	304.4	0.2	0.001	0.988	
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	304.6	0.5	0.001	0.989	
Cerrado, chaco, riverine, agriculture, cane, sec. vegetation, urban	304.7	0.5	0.001	0.991	
Cerrado, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban	305	0.9	<0.001	>0.991	
Cerrado, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	305.1	1	<0.001	>0.991	
Chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	305.8	1.6	<0.001	>0.991	
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	305.8	1.7	<0.001	>0.991	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	305.9	1.8	<0.001	>0.991	
Cerrado, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban	305.9	1.8	<0.001	>0.991	
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban	306.1	1.9	<0.001	>0.991	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban	306.5	2.4	<0.001	>0.991	
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, urban	306.6	2.5	<0.001	>0.991	
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	306.9	2.8	<0.001	>0.991	
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	307.2	3	<0.001	>0.991	
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	307.3	3.2	<0.001	>0.991	

Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban	307.5	3.4	<0.001	>0.991
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	307.5	3.4	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet)	307.7	3.5	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban	307.8	3.7	<0.001	>0.991
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban	307.9	3.7	<0.001	>0.991
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban	308	3.9	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, season (wet)	308.2	4	<0.001	>0.991
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	308.3	4.2	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, season (wet)	308.4	4.2	<0.001	>0.991
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	309	4.8	<0.001	>0.991
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	309.2	5.1	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	309.5	5.4	<0.001	>0.991
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	309.6	5.4	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	309.6	5.5	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	309.7	5.6	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, season (wet)	309.8	5.6	<0.001	>0.991
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	309.8	5.7	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban	310.2	6	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	310.2	6.1	<0.001	>0.991
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	310.3	6.1	<0.001	>0.991
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	310.4	6.3	<0.001	>0.991
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	311.1	6.9	<0.001	>0.991
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	311.3	7.2	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	311.3	7.2	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	311.7	7.5	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	311.9	7.8	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, season (wet)	312	7.9	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	313.7	9.6	<0.001	>0.991

Table 6. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of American Kestrel (*Falco sparverius*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Eucalyptus, cane, urban, season (wet)	306.3	0	0.113	0.113	0.119
Agriculture, eucalyptus, cane, urban, season (wet)	306.4	0.1	0.107	0.220	0.113
Eucalyptus, urban, season (wet)	306.6	0.3	0.097	0.317	0.102
Agriculture, eucalyptus, urban, season (wet)	307	0.7	0.078	0.395	0.082
Riverine, agriculture, eucalyptus, cane, urban, season (wet)	307.4	1.1	0.064	0.459	0.067
Riverine, agriculture, eucalyptus, urban, season (wet)	307.7	1.4	0.056	0.515	0.058
Riverine, eucalyptus, cane, urban, season (wet)	307.8	1.5	0.053	0.568	0.056
Cane, urban, season (wet)	308.3	2	0.042	0.610	0.044
Cane, season (wet)	308.3	2	0.041	0.650	0.043
Riverine, agriculture, cane, urban, season (wet)	308.4	2.1	0.040	0.690	0.042
Eucalyptus, season (wet)	309	2.7	0.029	0.719	0.031
Forest, riverine, agriculture, eucalyptus, urban, season (wet)	309.3	3	0.025	0.744	0.026
Forest, riverine, agriculture, eucalyptus, cane, urban, season (wet)	309.4	3.1	0.024	0.768	0.025
Forest, riverine, eucalyptus, cane, urban, season (wet)	309.4	3.1	0.024	0.792	0.025
Riverine, agriculture, eucalyptus, cane, urban, river level, season (wet)	309.4	3.2	0.023	0.815	0.025
Agriculture, eucalyptus, cane, season (wet)	309.7	3.4	0.021	0.836	0.022
Agriculture, cane, urban, season (wet)	309.8	3.5	0.019	0.855	0.020
Riverine, agriculture, eucalyptus, cane, season (wet)	309.9	3.6	0.018	0.873	0.019
Forest, riverine, agriculture, cane, urban, season (wet)	310.2	3.9	0.016	0.889	0.017
Forest, riverine, agriculture, eucalyptus, cane, urban, river level, season (wet)	310.9	4.7	0.011	0.900	0.012
Forest, riverine, agriculture, eucalyptus, urban, river level, season (wet)	311.2	4.9	0.010	0.910	0.010
Forest, riverine, eucalyptus, cane, urban, river level, season (wet)	311.4	5.1	0.009	0.919	0.009
Forest, riverine, agriculture, eucalyptus, cane, season (wet)	311.8	5.5	0.007	0.926	0.008
Forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, season (wet)	311.9	5.6	0.007	0.933	0.007

Forest, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	311.9	5.7	0.007	0.940	0.007
Forest, riverine, agriculture, cane, urban, river level, season (wet)	312.1	5.8	0.006	0.946	0.007
Forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	313	6.7	0.004	0.950	0.004
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	313.2	6.9	0.004	0.953	
Forest, riverine, agriculture, eucalyptus, cane, river level, season (wet)	313.2	6.9	0.004	0.957	
Eucalyptus, cane, season (wet)	313.2	7	0.004	0.960	
Forest, riverine, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	313.4	7.2	0.003	0.964	
Riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	313.5	7.2	0.003	0.967	
Riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	313.7	7.4	0.003	0.969	
Forest, riverine, agriculture, eucalyptus, sec. vegetation, urban, river level, season (wet)	313.9	7.6	0.003	0.972	
Forest, riverine, agriculture, cane, sec. vegetation, urban, river level, season (wet)	313.9	7.6	0.003	0.974	
Forest, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	314.1	7.8	0.002	0.977	
Forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	314.2	7.9	0.002	0.979	
Forest, agriculture, eucalyptus, cane, urban, season (wet)	314.4	8.2	0.002	0.981	
Forest, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	314.6	8.3	0.002	0.983	
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	315	8.7	0.001	0.984	
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	315.1	8.9	0.001	0.985	
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	315.3	9	0.001	0.986	
Eucalyptus, urban, river level	315.4	9.1	0.001	0.988	
Chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	315.5	9.2	0.001	0.989	
Forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	315.7	9.4	0.001	0.990	
Forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	315.7	9.4	0.001	0.991	
Forest, agriculture, eucalyptus, cane, urban, river level, season (wet)	315.9	9.6	<0.001	>0.991	
Forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	315.9	9.7	<0.001	>0.991	
Forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	316	9.7	<0.001	>0.991	
Eucalyptus, cane, urban, river level	316	9.8	<0.001	>0.991	
Forest, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	316.5	10.3	<0.001	>0.991	
Forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level, season (wet)	317.3	11	<0.001	>0.991	
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	317.4	11.1	<0.001	>0.991	
Agriculture, eucalyptus, cane, urban, river level	317.5	11.2	<0.001	>0.991	

Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	317.7	11.4	<0.001	>0.991
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	317.8	11.6	<0.001	>0.991
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	317.9	11.6	<0.001	>0.991
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	318	11.7	<0.001	>0.991
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	318.3	12	<0.001	>0.991
Forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	318.3	12	<0.001	>0.991
Cerrado, urban, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	318.4	12.2	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	318.5	12.3	<0.001	>0.991
Forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	318.6	12.3	<0.001	>0.991
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	318.7	12.4	<0.001	>0.991
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	319	12.7	<0.001	>0.991
Riverine, agriculture, eucalyptus, cane, urban, river level	319.1	12.9	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	319.3	13	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	321.7	15.4	<0.001	>0.991
Forest, riverine, agriculture, eucalyptus, cane, urban, river level	321.9	15.6	<0.001	>0.991
Cerrado, forest, chaco, riverine, pasture, agriculture, eucalyptus, sec. vegetation, urban, river level, season (wet)	322	15.8	<0.001	>0.991
Forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level	322.9	16.6	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	323.7	17.5	<0.001	>0.991
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	324.5	18.2	<0.001	>0.991
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	325.6	19.3	<0.001	>0.991
Forest, riverine, agriculture, eucalyptus, cane, urban, river level	326.3	20	<0.001	>0.991
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	326.5	20.3	<0.001	>0.991

Table 7. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Aplomado Falcon (*Falco femoralis*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Cerrado, chaco, riverine, agriculture, pasture, cane	114.3	0	0.260	0.260	0.274

Chaco, riverine, agriculture, pasture, cane	116.8	2.4	0.077	0.337	0.081
Cerrado, chaco, riverine, agriculture, pasture	117	2.7	0.068	0.405	0.072
Cerrado, chaco, riverine, pasture, cane	117.2	2.8	0.063	0.468	0.066
Cerrado, chaco, agriculture, pasture, cane	117.6	3.3	0.050	0.518	0.053
Cerrado, chaco, riverine, agriculture, pasture, cane, sec. vegetation	117.7	3.4	0.047	0.565	0.049
Cerrado, riverine, agriculture, pasture, cane, forest, sec. vegetation	118.2	3.9	0.037	0.601	0.039
Cerrado, chaco, riverine, agriculture, cane	118.3	4	0.036	0.637	0.038
Cerrado, riverine, agriculture, pasture, cane	118.3	4	0.035	0.672	0.037
Chaco, riverine, agriculture, pasture, cane, sec. vegetation	118.8	4.4	0.028	0.700	0.030
Cerrado, chaco, agriculture, pasture, cane, sec. vegetation	119	4.6	0.026	0.726	0.027
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation	119.1	4.8	0.023	0.749	0.025
Cerrado, chaco, riverine, agriculture, pasture, forest, cane, sec. vegetation	119.5	5.1	0.020	0.769	0.021
Cerrado, chaco, riverine, agriculture, pasture, forest, cane, season (wet)	119.5	5.2	0.020	0.789	0.021
Cerrado, chaco, riverine, pasture, cane, sec. vegetation	119.5	5.2	0.020	0.808	0.021
Cerrado, chaco, riverine, agriculture, pasture, cane, forest, sec. vegetation	119.7	5.4	0.018	0.826	0.019
Cerrado, chaco, riverine, agriculture, pasture, cane, season (wet), sec. vegetation	119.9	5.6	0.016	0.842	0.017
Cerrado, chaco, riverine, agriculture, cane, sec. vegetation	120.2	5.9	0.014	0.856	0.014
Cerrado, riverine, agriculture, pasture, cane, sec. vegetation	120.3	6	0.013	0.868	0.013
Cerrado, riverine, agriculture, pasture, forest, cane, season (wet), sec. vegetation	120.8	6.5	0.010	0.878	0.011
Cerrado, chaco, agriculture, pasture, cane, forest, sec. vegetation	121	6.7	0.009	0.888	0.010
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, season (wet), sec. vegetation	121.1	6.8	0.009	0.896	0.009
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, season (wet)	121.3	7	0.008	0.904	0.008
Chaco, riverine, agriculture, pasture, cane, forest, sec. vegetation	121.4	7.1	0.008	0.912	0.008
Cerrado, chaco, riverine, agriculture, pasture, forest, sec. vegetation	121.4	7.1	0.008	0.919	0.008
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	121.5	7.2	0.007	0.926	0.007
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, season (wet), sec. vegetation	121.8	7.4	0.006	0.933	0.007
Cerrado, chaco, riverine, pasture, cane, forest, sec. vegetation	121.8	7.5	0.006	0.939	0.007
Chaco, riverine, agriculture, pasture, forest, cane, season (wet), sec. vegetation	122.2	7.9	0.005	0.944	0.005
Cerrado, chaco, riverine, agriculture, cane, forest, sec. vegetation	122.3	8	0.005	0.949	0.005
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, season (wet), sec. vegetation	122.5	8.2	0.004	0.953	

Cerrado, chaco, agriculture, pasture, forest, cane, season (wet), sec. vegetation	122.9	8.5	0.004	0.956
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet)	123	8.7	0.003	0.960
Cerrado, chaco, riverine, agriculture, pasture, forest, season (wet), sec. vegetation	123.2	8.9	0.003	0.963
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, season (wet), river level	123.4	9.1	0.003	0.966
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, season (wet), river level	123.6	9.3	0.003	0.968
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	123.7	9.3	0.002	0.971
Cerrado, chaco, riverine, pasture, forest, cane, season (wet), sec. vegetation	123.7	9.4	0.002	0.973
Cerrado, urban, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	123.8	9.4	0.002	0.975
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	123.9	9.6	0.002	0.977
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet), river level	124.1	9.7	0.002	0.979
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, season (wet), sec. vegetation	124.2	9.9	0.002	0.981
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet), river level	124.3	9.9	0.002	0.983
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	124.4	0.1	0.002	0.985
Cerrado, chaco, riverine, agriculture, forest, cane, season (wet), sec. vegetation	124.4	0.1	0.002	0.986
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, season (wet), sec. vegetation	124.4	0.1	0.002	0.988
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	124.8	0.5	0.001	0.990
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, season (wet), sec. vegetation	124.8	0.5	0.001	0.991
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, season (wet), sec. vegetation	125.3	1	0.001	0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	125.4	1	0.001	0.993
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	125.4	1	0.001	0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	125.6	1.3	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, season (wet), sec. vegetation	125.7	1.4	<0.001	>0.994
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet), river level	126.4	2.1	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	126.5	2.1	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, season (wet), river level	126.9	2.6	<0.001	>0.994
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet), river level	127	2.7	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	127.2	2.8	<0.001	>0.994
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	127.9	3.6	<0.001	>0.994
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, season (wet), river level	128.1	3.8	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, season (wet), river level	128.1	3.8	<0.001	>0.994

Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	128.1	3.8	<0.001	>0.994
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	129.4	5.1	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	130.1	5.8	<0.001	>0.994

Table 8. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of White-tailed Hawk (*Geranoaetus albicaudatus*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Urban	169.3	0	0.135	0.135	0.143
Urban, river level, season (wet)	170.3	1	0.084	0.219	0.088
Urban, season (wet)	170.3	1	0.083	0.302	0.088
River level, season (wet)	170.3	1	0.082	0.384	0.087
Urban, river level	170.3	1	0.081	0.465	0.086
Season (wet)	170.4	1	0.080	0.545	0.085
Cane, urban, season (wet)	171.2	1.9	0.052	0.597	0.055
Cane, river level, season (wet)	171.6	2.3	0.043	0.640	0.046
Cane, urban, river level	171.7	2.4	0.040	0.680	0.042
Cane, urban, river level, season (wet)	171.8	2.5	0.039	0.719	0.041
Sec. vegetation, urban, river level, season (wet)	172	2.7	0.035	0.754	0.037
Cane, sec. vegetation, urban, season (wet)	172.5	3.2	0.027	0.781	0.029
Cane, sec. vegetation, river level, season (wet)	172.9	3.6	0.023	0.804	0.024
Cane, sec. vegetation, urban, river level, season (wet)	173.2	3.9	0.019	0.823	0.020
Cane, sec. vegetation, urban, river level	173.3	4	0.018	0.841	0.019
Forest, cane, urban, river level, season (wet)	173.4	4.1	0.018	0.859	0.019
Forest, sec. vegetation, urban, river level, season (wet)	173.5	4.2	0.017	0.875	0.017
Forest, cane, sec. vegetation, river level, season (wet)	173.7	4.4	0.015	0.891	0.016
Forest, cane, sec. vegetation, urban, season (wet)	173.9	4.6	0.014	0.904	0.014
Forest, cane, sec. vegetation, urban, river level, season (wet)	174.7	5.4	0.009	0.913	0.010

Forest, cane, sec. vegetation, urban, river level	174.8	5.5	0.009	0.922	0.009
Forest, riverine, sec. vegetation, urban, river level, season (wet)	174.9	5.6	0.008	0.931	0.009
Riverine, cane, sec. vegetation, urban, river level, season (wet)	175.2	5.9	0.007	0.938	0.008
Forest, riverine, cane, urban, river level, season (wet)	175.4	6	0.007	0.944	0.007
Forest, riverine, cane, sec. vegetation, urban, river level	175.6	6.3	0.006	0.951	
Forest, riverine, cane, sec. vegetation, river level, season (wet)	175.7	6.4	0.006	0.956	
Forest, riverine, cane, sec. vegetation, urban, season (wet)	176.4	7.1	0.004	0.960	
Forest, riverine, cane, sec. vegetation, urban, river level, season (wet)	176.4	7.1	0.004	0.963	
Cerrado, forest, riverine, sec. vegetation, urban, river level, season (wet)	176.9	7.6	0.003	0.966	
Cerrado, riverine, cane, sec. vegetation, urban, river level, season (wet)	177	7.7	0.003	0.969	
Cerrado, forest, cane, sec. vegetation, urban, river level, season (wet)	177.1	7.8	0.003	0.972	
Cerrado, forest, riverine, cane, urban, river level, season (wet)	177.3	8	0.003	0.975	
Cerrado, forest, riverine, cane, sec. vegetation, river level, season (wet)	177.4	8.1	0.002	0.977	
Cerrado, forest, riverine, cane, sec. vegetation, urban, river level	177.5	8.2	0.002	0.979	
Cerrado, forest, riverine, cane, sec. vegetation, urban, river level, season (wet)	178.3	9	0.002	0.981	
Cerrado, forest, riverine, cane, sec. vegetation, urban, season (wet)	178.3	9	0.002	0.982	
Cerrado, forest, chaco, riverine, sec. vegetation, urban, river level, season (wet)	178.4	9.1	0.002	0.984	
Forest, chaco, riverine, cane, sec. vegetation, urban, river level, season (wet)	178.5	9.2	0.001	0.985	
Cerrado, forest, chaco, riverine, cane, sec. vegetation, urban, river level	178.8	9.5	0.001	0.986	
Cerrado, forest, chaco, riverine, cane, sec. vegetation, urban, season (wet)	178.8	9.5	0.001	0.987	
Cerrado, forest, chaco, cane, sec. vegetation, urban, river level, season (wet)	178.9	9.6	0.001	0.989	
Cerrado, forest, chaco, riverine, cane, urban, river level, season (wet)	178.9	9.6	0.001	0.990	
Cerrado, chaco, riverine, cane, sec. vegetation, urban, river level, season (wet)	178.9	9.6	0.001	0.991	
Cerrado, forest, chaco, riverine, cane, sec. vegetation, river level, season (wet)	179	9.7	0.001	0.992	
Cerrado, forest, chaco, riverine, cane, sec. vegetation, urban, river level, season (wet)	179.5	10.2	<0.001	>0.992	
Forest, chaco, riverine, pasture, cane, sec. vegetation, urban, river level, season (wet)	180.1	10.8	<0.001	>0.992	
Cerrado, forest, riverine, pasture, cane, sec. vegetation, urban, river level, season (wet)	180.2	10.8	<0.001	>0.992	
Cerrado, forest, chaco, riverine, pasture, sec. vegetation, urban, river level, season (wet)	180.2	10.9	<0.001	>0.992	
Cerrado, forest, chaco, pasture, cane, sec. vegetation, urban, river level, season (wet)	180.5	11.2	<0.001	>0.992	
Cerrado, forest, chaco, riverine, pasture, cane, sec. vegetation, urban, season (wet)	180.7	11.4	<0.001	>0.992	

Cerrado, forest, chaco, riverine, pasture, cane, sec. vegetation, urban, river level	180.8	11.5	<0.001	>0.992
Cerrado, forest, chaco, riverine, pasture, cane, urban, river level, season (wet)	180.8	11.5	<0.001	>0.992
Cerrado, chaco, riverine, pasture, cane, sec. vegetation, urban, river level, season (wet)	181	11.7	<0.001	>0.992
Cerrado, forest, chaco, riverine, pasture, cane, sec. vegetation, river level, season (wet)	181.2	11.9	<0.001	>0.992
Cerrado, forest, chaco, riverine, pasture, cane, sec. vegetation, urban, river level, season (wet)	181.6	12.3	<0.001	>0.992
Forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	181.7	12.4	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, cane, sec. vegetation, urban, river level, season (wet)	181.7	12.4	<0.001	>0.992
Cerrado, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	181.9	12.5	<0.001	>0.992
Cerrado, forest, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	182	12.7	<0.001	>0.992
Cerrado, forest, chaco, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	182.4	13.1	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, urban, river level, season (wet)	182.4	13.1	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	182.4	13.1	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, river level, season (wet)	182.4	13.1	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, season (wet)	182.6	13.3	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level	182.7	13.4	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	183.3	14	<0.001	>0.992
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	183.9	14.6	<0.001	>0.992
Cerrado, urban, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	183.9	14.6	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	183.9	14.6	<0.001	>0.992
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	183.9	14.6	<0.001	>0.992
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	184	14.7	<0.001	>0.992
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	184.2	14.9	<0.001	>0.992
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	184.2	14.9	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	184.5	15.2	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	184.6	15.3	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	184.7	15.4	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level, season (wet)	185.1	15.8	<0.001	>0.992
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	185.9	16.6	<0.001	>0.992

Table 9. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Snail Kite (*Rosthramus sociabilis*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated negative binomial mixture ($n = 195$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Cerrado, riverine, pasture, river level	152	0	0.226	0.226	0.239
Cerrado, pasture, river level	152.4	0.5	0.178	0.404	0.189
Cerrado, sec. vegetation, riverine, pasture, river level	153.3	1.3	0.116	0.520	0.122
Cerrado, riverine, agriculture, pasture, sec. vegetation, river level	154.3	2.3	0.070	0.590	0.074
Cerrado, sec. vegetation, pasture, river level	154.7	2.7	0.058	0.648	0.062
Cerrado, forest, riverine, agriculture, pasture, river level	155.2	3.2	0.046	0.694	0.048
Cerrado, riverine, pasture, agriculture, river level	156.1	4.1	0.028	0.722	0.030
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, forest, river level	156.1	4.2	0.028	0.750	0.030
Cerrado, riverine, agriculture, pasture, sec. vegetation, river level, forest	156.2	4.2	0.028	0.778	0.029
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, river level	156.5	4.6	0.023	0.801	0.024
Cerrado, forest, riverine, pasture, sec. vegetation, river level	156.6	4.6	0.023	0.824	0.024
Cerrado, chaco, riverine, agriculture, pasture, river level, forest	156.6	4.6	0.022	0.846	0.024
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, river level, season (wet)	156.6	4.6	0.022	0.868	0.023
Cerrado, chaco, riverine, pasture, sec. vegetation, river level, forest	156.7	4.7	0.022	0.890	0.023
Cerrado, forest, agriculture, pasture, sec. vegetation, river level	157.8	5.8	0.012	0.902	0.013
Riverine, pasture, river level	158.1	6.2	0.010	0.912	0.011
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, river level, season (wet)	158.5	6.5	0.009	0.921	0.009
Cerrado, chaco, riverine, pasture, sec. vegetation, forest, river level, season (wet)	158.6	6.6	0.008	0.929	0.009
Cerrado, chaco, riverine, agriculture, pasture, forest, river level, season (wet)	158.6	6.7	0.008	0.937	0.008
Cerrado, sec. vegetation, pasture, agriculture, river level	158.7	6.7	0.008	0.945	0.008
Cerrado, forest, chaco, riverine, agriculture, pasture, urban, river level, season (wet)	158.9	6.9	0.007	0.952	
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	159	7	0.007	0.958	
Cerrado, sec. vegetation, riverine, agriculture, river level	159	7.1	0.007	0.965	
Cerrado, riverine, agriculture, pasture, sec. vegetation, forest, river level, season (wet)	159.2	7.3	0.006	0.971	

Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level	159.7	7.8	0.005	0.976
Sec. vegetation, riverine, pasture, river level	159.8	7.9	0.004	0.980
Cerrado, forest, riverine, agriculture, sec. vegetation, river level	160.7	8.8	0.003	0.983
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	160.8	8.9	0.003	0.985
Cerrado, forest, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	161.5	9.5	0.002	0.987
Cerrado, forest, chaco, riverine, pasture, sec. vegetation, urban, river level, season (wet)	161.5	9.5	0.002	0.989
Sec. vegetation, riverine, pasture, agriculture, river level	162.1	10.1	0.001	0.991
Cerrado, chaco, agriculture, pasture, sec. vegetation, forest, river level, season (wet)	162.2	10.2	0.001	0.992
Cerrado, chaco, agriculture, pasture, sec. vegetation, river level, forest	162.2	10.3	0.001	0.993
Forest, riverine, agriculture, pasture, sec. vegetation, river level	162.3	10.3	0.001	0.995
Cerrado, chaco, riverine, agriculture, sec. vegetation, river level, forest	162.5	10.6	0.001	0.996
Cerrado, riverine, river level	162.8	10.9	<0.001	>0.996
Pasture, river level	162.8	10.9	<0.001	>0.996
Cerrado, forest, chaco, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	164.3	12.3	<0.001	>0.996
Cerrado, river level	164.4	12.5	<0.001	>0.996
Cerrado, sec. vegetation, riverine, river level	164.6	12.6	<0.001	>0.996
Cerrado, chaco, riverine, agriculture, sec. vegetation, forest, river level, season (wet)	165	13.1	<0.001	>0.996
Chaco, riverine, agriculture, pasture, sec. vegetation, river level, forest	165.3	13.3	<0.001	>0.996
Cerrado, forest, chaco, riverine, agriculture, sec. vegetation, urban, river level, season (wet)	167.3	15.4	<0.001	>0.996
Chaco, riverine, agriculture, pasture, sec. vegetation, forest, river level, season (wet)	168.5	16.5	<0.001	>0.996
Forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	169	17	<0.001	>0.996
Cerrado, pasture	171.9	19.9	<0.001	>0.996
Cerrado, riverine, pasture	173.2	21.3	<0.001	>0.996
Cerrado, sec. vegetation, riverine, pasture, agriculture	174	22	<0.001	>0.996
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, forest	174.3	22.3	<0.001	>0.996
Cerrado, forest, riverine, agriculture, pasture, sec. vegetation	174.3	22.3	<0.001	>0.996
Cerrado, sec. vegetation, riverine, pasture	175.1	23.1	<0.001	>0.996
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, forest, season (wet)	176.8	24.9	<0.001	>0.996
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, season (wet)	179	27.1	<0.001	>0.996

Table 10. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Black-collared Hawk (*Busarellus nigricolis*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated Poisson mixture ($n = 195$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Forest, chaco, pasture, season (wet)	110,3	0,0	0.160	0.160	0.169
Cerrado, forest, chaco, pasture, season (wet)	111,0	0,7	0.112	0.272	0.119
Forest, chaco, pasture, sec. vegetation, season (wet)	111,7	1,4	0.079	0.352	0.084
Cerrado, forest, chaco, pasture, sec. vegetation, season (wet)	111,8	1,4	0.078	0.429	0.082
Forest, chaco, pasture, sec. vegetation, agriculture, season (wet)	113,0	2,7	0.042	0.471	0.044
Cerrado, forest, chaco, pasture	113,3	3,0	0.036	0.508	0.038
Forest, pasture, season (wet)	113,4	3,1	0.034	0.541	0.036
Forest, chaco, pasture	113,5	3,2	0.033	0.574	0.035
Chaco, pasture, season (wet)	113,5	3,2	0.032	0.606	0.034
Cerrado, forest, chaco, sec. vegetation, season (wet)	113,9	3,5	0.027	0.634	0.029
Cerrado, forest, chaco, pasture, sec. vegetation, urban, season (wet)	113,9	3,6	0.027	0.660	0.028
Forest, chaco, season (wet)	113,9	3,6	0.026	0.687	0.028
Cerrado, forest, pasture, sec. vegetation, season (wet)	114,2	3,9	0.023	0.710	0.024
Cerrado, forest, pasture, season (wet)	114,3	3,9	0.023	0.732	0.024
Cerrado, forest, chaco, pasture, sec. vegetation	114,3	3,9	0.022	0.755	0.024
Cerrado, forest, chaco, pasture, sec. vegetation, agriculture, season (wet)	114,3	4,0	0.022	0.776	0.023
Cerrado, forest, chaco, pasture, urban, river level, season (wet)	114,3	4,0	0.022	0.798	0.023
Cerrado, forest, chaco, pasture, sec. vegetation, river level, season (wet)	114,4	4,1	0.021	0.819	0.022
Cerrado, forest, chaco, pasture, urban, agriculture, season (wet)	114,6	4,2	0.019	0.838	0.020
Cerrado, forest, chaco, pasture, sec. vegetation, urban, season (wet)	114,7	4,3	0.018	0.856	0.019
Forest, chaco, pasture, sec. vegetation, urban, agriculture, season (wet)	115,2	4,9	0.014	0.870	0.015
Cerrado, forest, chaco, pasture, sec. vegetation, urban, river level	115,3	5,0	0.013	0.884	0.014
Cerrado, forest, chaco, season (wet)	115,5	5,2	0.012	0.896	0.013
Cerrado, forest, chaco, pasture, agriculture, season (wet)	115,5	5,2	0.012	0.908	0.013

Cerrado, forest, chaco, pasture, sec. vegetation, urban, river level, season (wet)	115,6	5,3	0.011	0.919	0.012
Cerrado, forest, chaco, sec. vegetation, agriculture, season (wet)	115,9	5,6	0.010	0.929	0.010
Cerrado, forest, chaco, pasture, sec. vegetation, agriculture	116,0	5,6	0.010	0.938	0.010
Cerrado, chaco, pasture, season (wet)	116,3	5,9	0.008	0.947	0.009
Cerrado, forest, pasture, sec. vegetation, agriculture, season (wet)	116,7	6,4	0.006	0.953	
Cerrado, chaco, pasture, sec. vegetation, agriculture, season (wet)	117,3	7,0	0.005	0.958	
Cerrado, chaco, pasture, sec. vegetation, urban, agriculture, season (wet)	117,7	7,3	0.004	0.962	
Cerrado, forest, chaco, pasture, agriculture, sec. vegetation, urban, river level, season (wet)	118,1	7,7	0.003	0.965	
Cerrado, forest, chaco, riverine, pasture, agriculture, urban, river level, season (wet)	118,1	7,8	0.003	0.969	
Cerrado, forest, pasture, sec. vegetation, urban, agriculture, season (wet)	118,2	7,9	0.003	0.972	
Cerrado, chaco, pasture, sec. vegetation, season (wet)	118,3	7,9	0.003	0.975	
Cerrado, forest, chaco, sec. vegetation, urban, agriculture, season (wet)	118,6	8,2	0.003	0.977	
Cerrado, forest, chaco, sec. vegetation, urban, river level, season (wet)	118,7	8,4	0.002	0.980	
Cerrado, forest, chaco, riverine, pasture, sec. vegetation, urban, river level, season (wet)	118,8	8,5	0.002	0.982	
Forest, chaco, pasture, sec. vegetation, urban, river level, season (wet)	118,8	8,5	0.002	0.984	
Cerrado, forest, pasture, sec. vegetation, urban, river level, season (wet)	119,1	8,8	0.002	0.986	
Cerrado, forest, chaco, riverine, pasture, agriculture, sec. vegetation, urban, season (wet)	119,1	8,8	0.002	0.988	
Cerrado, forest, chaco, riverine, pasture, agriculture, sec. vegetation, urban, river level	119,1	8,8	0.002	0.990	
Forest, chaco, riverine, pasture, agriculture, sec. vegetation, urban, river level, season (wet)	119,2	8,8	0.002	0.992	
Cerrado, forest, chaco, pasture, sec. vegetation, urban, agriculture	119,3	9,0	0.002	0.994	
Cerrado, forest, chaco, riverine, pasture, agriculture, sec. vegetation, river level, season (wet)	119,6	9,3	0.002	0.996	
Cerrado, chaco, riverine, pasture, agriculture, sec. vegetation, urban, river level, season (wet)	119,7	9,4	0.001	0.997	
Cerrado, chaco, pasture, sec. vegetation, urban, river level, season (wet)	120,5	10,2	0.001	0.998	
Cerrado, forest, chaco, riverine, pasture, agriculture, sec. vegetation, urban, river level, season (wet)	121,1	10,8	0.001	0.999	
Cerrado, forest, riverine, pasture, agriculture, sec. vegetation, urban, river level, season (wet)	121,4	11,1	<0.001	>0.999	
Cerrado, forest, chaco, agriculture, riverine, sec. vegetation, urban, river level, season (wet)	122,3	12,0	<0.000	>0.999	

Table 11. Backwards-stepwise model selection based on conditional likelihood AICc on the abundance term of the multiple covariate abundance models of Great Black Hawk (*Buteogallus urubitinga*). Rescaled AICc weights are given for models within 0.95 cumulative weight. All models based on the binomial–zero-inflated Poisson mixture ($n = 195$ samples).

Covariates	AICc	dAICc	Weight	Cumulative weight	Rescaled weight
Riverine, agriculture, sec. vegetation	107.2	0	0.232	0.232	0.246
Riverine, agriculture, sec. vegetation, urban	108.2	1.1	0.136	0.369	0.144
Riverine, agriculture, sec. vegetation, season (wet)	108.9	1.8	0.096	0.465	0.102
Riverine, sec. vegetation, urban	109.6	2.5	0.068	0.532	0.072
Riverine, agriculture, sec. vegetation, urban, season (wet)	110.1	3	0.053	0.585	0.056
Cerrado, riverine, agriculture, sec. vegetation, season (wet)	110.2	3	0.051	0.636	0.054
Cerrado, riverine, agriculture, sec. vegetation, urban	110.5	3.4	0.043	0.680	0.046
Riverine	111.3	4.1	0.030	0.709	0.031
Riverine, sec. vegetation, urban, season (wet)	111.4	4.3	0.028	0.737	0.029
Riverine, agriculture, urban	111.7	4.6	0.024	0.760	0.025
Sec. vegetation	111.9	4.7	0.022	0.783	0.024
Cerrado, riverine, agriculture, sec. vegetation, urban, season (wet)	112.2	5	0.019	0.802	0.020
Agriculture, sec. vegetation, urban	112.2	5	0.019	0.821	0.020
Cerrado, forest, riverine, agriculture, sec. vegetation, season (wet)	112.3	5.2	0.018	0.838	0.019
Cerrado, riverine, sec. vegetation, urban, season (wet)	112.5	5.3	0.016	0.855	0.017
Cerrado, forest, riverine, agriculture, sec. vegetation, urban	112.6	5.4	0.016	0.870	0.017
Agriculture, sec. vegetation, urban, season (wet)	112.7	5.5	0.015	0.885	0.016
Forest, riverine, agriculture, sec. vegetation, urban, season (wet)	112.7	5.5	0.015	0.900	0.016
Cerrado, agriculture, sec. vegetation, urban, season (wet)	113	5.9	0.012	0.912	0.013
Riverine, agriculture, urban, season (wet)	113.1	5.9	0.012	0.925	0.013
Cerrado, forest, riverine, agriculture, sec. vegetation, urban, season (wet)	114.2	7.1	0.007	0.931	0.007
Cerrado, chaco, riverine, agriculture, sec. vegetation, urban, season (wet)	114.3	7.2	0.006	0.938	0.007
Cerrado, riverine, agriculture, urban, season (wet)	114.4	7.2	0.006	0.944	0.007
Cerrado, forest, chaco, riverine, agriculture, sec. vegetation, season (wet)	114.4	7.2	0.006	0.950	

Cerrado, forest, riverine, sec. vegetation, urban, season (wet)	114.5	7.4	0.006	0.956
Cerrado, forest, chaco, riverine, agriculture, sec. vegetation, urban	114.7	7.5	0.005	0.962
Forest, chaco, riverine, agriculture, sec. vegetation, urban, season (wet)	114.8	7.6	0.005	0.967
Cerrado, forest, agriculture, sec. vegetation, urban, season (wet)	115	7.8	0.005	0.972
Cerrado, forest, chaco, riverine, sec. vegetation, urban, season (wet)	116.1	8.9	0.003	0.974
Cerrado, forest, chaco, riverine, agriculture, sec. vegetation, urban, season (wet)	116.4	9.3	0.002	0.976
Cerrado, forest, riverine, agriculture, pasture, sec. vegetation, urban, season (wet)	116.5	9.3	0.002	0.979
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, urban, season (wet)	116.5	9.4	0.002	0.981
Cerrado, forest, riverine, agriculture, urban, season (wet)	116.6	9.4	0.002	0.983
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, season (wet)	116.6	9.5	0.002	0.985
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban	116.9	9.7	0.002	0.987
Forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, season (wet)	117	9.8	0.002	0.988
Cerrado, forest, chaco, agriculture, sec. vegetation, urban, season (wet)	117.2	0	0.002	0.990
Cerrado, forest, chaco, riverine, agriculture, pasture, urban, season (wet)	117.4	0.3	0.001	0.991
Cerrado, forest, chaco, riverine, agriculture, urban, season (wet)	117.6	0.4	0.001	0.993
Cerrado, forest, chaco, riverine, pasture, sec. vegetation, urban, season (wet)	118.1	0.9	0.001	0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, season (wet)	118.7	1.5	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, sec. vegetation, urban, river level, season (wet)	118.8	1.6	<0.001	>0.994
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	118.8	1.6	<0.001	>0.994
Cerrado, forest, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	118.8	1.7	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level	118.8	1.7	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, river level, season (wet)	118.9	1.8	<0.001	>0.994
Forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	119.2	2	<0.001	>0.994
Cerrado, forest, chaco, agriculture, pasture, sec. vegetation, urban, season (wet)	119.3	2.1	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, urban, river level, season (wet)	119.8	2.7	<0.001	>0.994
Cerrado, forest, chaco, riverine, pasture, sec. vegetation, urban, river level, season (wet)	120.4	3.2	<0.001	>0.994
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	121.1	3.9	<0.001	>0.994
Cerrado, forest, chaco, agriculture, pasture, sec. vegetation, urban, river level, season (wet)	121.5	4.3	<0.001	>0.994

Appendix E

Table 1. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for *Cathartes* vultures (*C. aura* and *C. burrovianus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ observations), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma=0$ is the Poisson case).

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	0.079	λ	3.574	3.438	3.365	(2.927, 4.059)
		p	0.781	0.816	0.826	(0.691, 0.891)
		ϕ	0.058	0.059	0.055	(<0.000, 0.138)
		σ	1.288	1.305	1.280	(0.951, 1.775)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, river level	0.073	λ	3.377	3.362	3.365	(2.813, 3.936)
		p	0.831	0.839	0.847	(0.743, 0.918)
		ϕ	<0.000	<0.000	<0.000	(<0.000, 0)
		σ	1.301	1.329	1.265	(0.955, 1.903)
Cerrado, forest, agriculture, pasture, eucalyptus, sec. vegetation, river level	0.072	λ	3.876	3.586	3.510	(2.942, 4.398)
		p	0.725	0.789	0.803	(0.644, 0.869)
		ϕ	0.060	0.065	0.064	(<0.000, 0.139)
		σ	1.310	1.324	1.293	(0.929, 1.822)
Cerrado, forest, agriculture, pasture, eucalyptus, river level	0.072	λ	3.702	3.484	3.477	(3.024, 4.011)
		p	0.764	0.816	0.818	(0.728, 0.886)
		ϕ	0.064	0.068	0.067	(<0.000, 0.145)
		σ	1.300	1.302	1.298	(0.998, 1.708)
Cerrado, agriculture, pasture, eucalyptus, river level	0.070	λ	3.264	3.312	3.269	(2.8, 3.911)
		p	0.850	0.846	0.857	(0.731, 0.908)
		ϕ	0.053	0.061	0.057	(<0.000, 0.143)

		σ	1.332	1.335	1.295	(0.982, 1.812)
		λ	3.620	3.461	3.451	(2.929, 4.121)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.064	p	0.765	0.812	0.817	(0.724, 0.888)
		ϕ	0.047	0.061	0.054	(<0.000, 0.145)
		σ	1.295	1.280	1.232	(0.962, 1.697)
		λ	4.461	3.963	3.723	(3.111, 5.654)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, river level	0.050	p	0.628	0.728	0.755	(0.51, 0.844)
		ϕ	0.054	0.062	0.056	(<0.000, 0.14)
		σ	1.298	1.304	1.255	(0.972, 1.804)
		λ	3.876	3.574	3.509	(2.923, 4.366)
Cerrado, forest, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.048	p	0.723	0.787	0.801	(0.635, 0.895)
		ϕ	0.065	0.058	0.056	(<0.000, 0.139)
		σ	1.259	1.333	1.284	(0.94, 1.838)
		λ	3.552	3.412	3.395	(2.929, 4.022)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, river level	0.039	p	0.792	0.823	0.830	(0.746, 0.885)
		ϕ	0.058	0.058	0.057	(<0.000, 0.135)
		σ	1.271	1.299	1.268	(0.972, 1.736)
		λ	3.408	3.402	3.303	(2.812, 4.127)
Cerrado, riverine, agriculture, pasture, eucalyptus, river level	0.037	p	0.813	0.832	0.846	(0.715, 0.899)
		ϕ	0.055	0.063	0.059	(<0.000, 0.15)
		σ	1.300	1.307	1.287	(0.96, 1.738)
		λ	3.190	3.276	3.254	(2.739, 3.769)
Cerrado, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	0.033	p	0.859	0.851	0.856	(0.766, 0.923)
		ϕ	0.047	0.060	0.057	(<0.000, 0.144)
		σ	1.328	1.318	1.282	(0.971, 1.73)
		λ	4.229	4.094	3.839	(3.303, 5.982)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.029	p	0.656	0.704	0.725	(0.462, 0.827)
		ϕ	0.042	0.060	0.057	(<0.000, 0.157)
		σ	1.312	1.275	1.271	(0.931, 1.7)
Riverine, agriculture, pasture, eucalyptus, river level	0.027	λ	3.317	3.352	3.330	(2.821, 3.904)

		p	0.833	0.845	0.852	(0.749, 0.916)
		ϕ	0.049	0.067	0.064	(<0.000, 0.147)
		σ	1.346	1.295	1.274	(0.975, 1.691)
		λ	3.823	3.556	3.530	(2.911, 4.263)
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.025	p	0.730	0.794	0.807	(0.679, 0.879)
		ϕ	0.057	0.063	0.063	(<0.000, 0.136)
		σ	1.293	1.312	1.254	(0.951, 1.87)
		λ	3.688	3.452	3.430	(2.918, 4.089)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	0.025	p	0.772	0.815	0.823	(0.715, 0.893)
		ϕ	0.071	0.061	0.065	(<0.000, 0.141)
		σ	1.253	1.314	1.279	(0.982, 1.733)
		λ	3.419	3.376	3.345	(2.91, 3.874)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level	0.023	p	0.804	0.839	0.844	(0.747, 0.909)
		ϕ	0.051	0.062	0.065	(<0.000, 0.132)
		σ	1.285	1.275	1.258	(0.937, 1.652)
		λ	3.488	3.371	3.331	(2.84, 3.987)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	0.022	p	0.792	0.836	0.841	(0.745, 0.907)
		ϕ	0.048	0.067	0.065	(<0.000, 0.156)
		σ	1.295	1.266	1.233	(0.928, 1.699)
		λ	3.563	3.375	3.344	(2.847, 3.957)
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.022	p	0.780	0.820	0.827	(0.728, 0.889)
		ϕ	0.054	0.052	0.047	(<0.000, 0.141)
		σ	1.286	1.324	1.285	(0.951, 1.777)
		λ	3.333	3.396	3.362	(2.81, 4.038)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus	0.017	p	0.828	0.828	0.847	(0.7, 0.894)
		ϕ	0.039	0.061	0.059	(<0.000, 0.146)
		σ	1.396	1.334	1.276	(0.974, 1.836)
		λ	4.004	3.748	3.722	(3.15, 4.482)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	0.016	p	0.702	0.759	0.765	(0.668, 0.847)
		ϕ	0.059	0.062	0.065	(<0.000, 0.139)

		σ	1.240	1.259	1.239	(0.924, 1.627)
		λ	3.524	3.403	3.372	(2.871, 4.069)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	0.015	p	0.774	0.819	0.824	(0.734, 0.883)
		ϕ	0.039	0.060	0.056	(<0.000, 0.146)
		σ	1.346	1.299	1.260	(0.945, 1.782)
		λ	3.189	3.356	3.284	(2.765, 4.2)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation	0.014	p	0.867	0.838	0.853	(0.673, 0.928)
		ϕ	0.046	0.061	0.064	(<0.000, 0.145)
		σ	1.355	1.331	1.279	(0.962, 1.869)
		λ	3.559	3.405	3.407	(2.816, 4.023)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	0.013	p	0.772	0.820	0.826	(0.744, 0.893)
		ϕ	0.043	0.057	0.056	(<0.000, 0.134)
		σ	1.330	1.323	1.282	(0.954, 1.885)
		λ	4.205	3.819	3.680	(3.074, 5.262)
Forest, riverine, agriculture, pasture, eucalyptus, sec. vegetation, river level	0.013	p	0.661	0.750	0.776	(0.554, 0.864)
		ϕ	0.054	0.061	0.059	(<0.000, 0.141)
		σ	1.330	1.329	1.284	(0.98, 1.861)
		λ	3.933	3.758	3.730	(3.109, 4.559)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, urban, river level, season (wet)	0.011	p	0.713	0.764	0.773	(0.633, 0.851)
		ϕ	0.056	0.070	0.068	(<0.000, 0.151)
		σ	1.274	1.246	1.212	(0.902, 1.672)
		λ	3.446	3.359	3.355	(2.759, 3.889)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, sec. vegetation, urban, river level	0.010	p	0.808	0.838	0.842	(0.762, 0.906)
		ϕ	0.050	0.061	0.058	(<0.000, 0.138)
		σ	1.323	1.314	1.280	(0.98, 1.706)
		λ	3.942	3.626	3.551	(3.017, 4.436)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level, season (wet)	0.010	p	0.713	0.784	0.793	(0.664, 0.869)
		ϕ	0.062	0.068	0.071	(<0.000, 0.14)
		σ	1.268	1.240	1.200	(0.948, 1.658)
Forest, riverine, agriculture, pasture, eucalyptus, river level	0.009	λ	3.113	3.283	3.253	(2.765, 3.868)

		p	0.880	0.858	0.871	(0.756, 0.919)
		ϕ	0.040	0.061	0.060	(<0.000, 0.136)
		σ	1.391	1.318	1.290	(1.021, 1.722)
		λ	3.620	3.419	3.390	(2.916, 3.976)
Cerrado, riverine, pasture, eucalyptus, river level	0.009	p	0.783	0.829	0.831	(0.766, 0.881)
		ϕ	0.061	0.065	0.064	(<0.000, 0.142)
		σ	1.360	1.361	1.320	(1.023, 1.761)
		λ	3.528	3.423	3.386	(2.868, 4.139)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.009	p	0.780	0.819	0.825	(0.72, 0.884)
		ϕ	0.045	0.060	0.062	(<0.000, 0.135)
		σ	1.322	1.310	1.295	(0.964, 1.705)
		λ	3.420	3.336	3.295	(2.791, 3.961)
Cerrado, riverine, agriculture, pasture, eucalyptus	0.009	p	0.805	0.832	0.839	(0.735, 0.9)
		ϕ	<0.000	<0.000	<0.000	(<0.000, 0)
		σ	1.377	1.372	1.339	(1.031, 1.788)
		λ	3.273	3.311	3.256	(2.657, 4.027)
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.008	p	0.843	0.839	0.859	(0.68, 0.92)
		ϕ	0.048	0.051	0.046	(<0.000, 0.136)
		σ	1.319	1.407	1.337	(1.01, 2.269)
		λ	4.255	4.061	3.867	(3.208, 5.651)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.008	p	0.660	0.715	0.739	(0.504, 0.846)
		ϕ	0.058	0.063	0.059	(<0.000, 0.138)
		σ	1.259	1.268	1.235	(0.936, 1.732)
		λ	4.129	3.843	3.733	(3.06, 5.05)
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level	0.008	p	0.662	0.744	0.761	(0.552, 0.866)
		ϕ	0.041	0.060	0.059	(<0.000, 0.133)
		σ	1.340	1.294	1.251	(0.985, 1.761)
		λ	3.728	3.590	3.532	(2.994, 4.172)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.007	p	0.740	0.786	0.787	(0.703, 0.873)
		ϕ	0.047	0.064	0.067	(<0.000, 0.131)

σ	1.292	1.253	1.244	(0.946, 1.632)
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Table 2. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Black Vulture (*Coragyps atratus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ observations), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Riverine, pasture, cane, sec. vegetation, season (wet)	0.209	λ	3.166	174.878	4.066	(0.944, 7.386)
		p	0.643	0.629	0.627	(0.522, 0.742)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	10.301	20.503	7.743	(3.792, 31.552)
Riverine, pasture, cane, sec. vegetation, urban, season (wet)	0.146	λ	3.249	4.519	4.142	(1.913, 7.826)
		p	0.637	0.630	0.626	(0.536, 0.735)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	10.104	9.335	7.008	(4.034, 19.707)
Riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.114	λ	3.199	7.049	4.376	(1.272, 8.106)
		p	0.629	0.616	0.625	(0.483, 0.729)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	10.630	26.893	7.891	(4.138, 29.932)

Riverine, pasture, eucalyptus, cane, sec. vegetation, season (wet)	0.092	λ	3.148	>1000	3.985	(1.904, 7.495)
		p	0.699	0.667	0.670	(0.562, 0.775)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	9.342	9.512	7.737	(4.048, 19.995)
Forest, riverine, pasture, eucalyptus, cane, sec. vegetation, season (wet)	0.047	λ	2.819	5.582	3.979	(1.249, 8.535)
		p	0.661	0.650	0.652	(0.549, 0.747)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	11.031	197.99 3	7.472	(3.726, 27.127)
Forest, riverine, pasture, cane, sec. vegetation, urban, season (wet)	0.046	λ	2.957	5.803	4.353	(0.976, 7.556)
		p	0.603	0.604	0.613	(0.499, 0.713)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	12.041	20.684	7.742	(4.083, 51.079)
Cerrado, forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.036	λ	3.199	4.338	4.257	(1.431, 7.392)
		p	0.646	0.636	0.632	(0.532, 0.756)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	9.593	13.664	7.121	(3.542, 26.335)
Forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.035	λ	3.821	5.420	4.306	(1.844, 8.205)
		p	0.629	0.632	0.631	(0.536, 0.734)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)

		σ	8.508	10.070	7.529	(3.870, 19.410)
		λ	0.092	91.332	1.571	(<0.000, 8.049)
		p	0.670	0.696	0.695	(0.401, 0.996)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	403.730	>1000	23.167	(4.786, >1000)
		λ	3.732	36.920	4.354	(1.484, 8.091)
		p	0.603	0.600	0.596	(0.491, 0.718)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	8.978	14.805	7.093	(3.880, 29.513)
		λ	2.995	29.308	4.276	(1.980, 7.760)
		p	0.703	0.679	0.684	(0.549, 0.790)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	9.115	10.367	6.508	(3.388, 18.512)
		λ	0.003	0.139	0.003	(0.003, 0.003)
		p	0.616	0.619	0.616	(0.616, 0.616)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	15948.180	79.960	0.002	(0.002, 0.002)
		λ	3.180	4.344	4.201	(1.844, 7.259)
		p	0.669	0.669	0.672	(0.568, 0.761)

		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	9.087	137.72 0	6.035	(3.554, 18.502)
		λ	3.071	4.719	4.126	(1.991, 7.352)
		p	0.689	0.679	0.683	(0.578, 0.791)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet)	0.018	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	8.649	60.873	6.166	(3.118, 15.434)
		λ	3.654	4.613	4.402	(1.464, 7.417)
		p	0.628	0.636	0.629	(0.535, 0.749)
Forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.016	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	8.044	12.234	6.410	(3.164, 24.886)
		λ	2.876	10.892	3.764	(1.412, 7.138)
		p	0.696	0.675	0.674	(0.582, 0.777)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, season (wet)	0.016	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	8.776	12.812	6.754	(3.752, 25.951)
		λ	1.905	4.941	3.975	(1.419, 7.114)
		p	0.701	0.667	0.663	(0.557, 0.781)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.014	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	15.371	12.456	6.535	(3.577, 29.663)
Forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.014	λ	2.000	4.286	4.053	(1.610, 7.259)

		p	0.629	0.634	0.637	(0.537, 0.747)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	16.315	10.910	6.525	(3.526, 19.709)
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.014	λ	2.798	46.265	4.765	(1.704, 8.369)
		p	0.624	0.620	0.616	(0.523, 0.726)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	12.514	71.739	6.604	(3.601, 21.633)
		λ	2.562	5.974	3.883	(0.788, 6.784)
Cerrado, forest, riverine, pasture, eucalyptus, cane, sec. vegetation, urban	0.011	p	0.659	0.653	0.655	(0.520, 0.764)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	11.798	26.996	7.130	(3.793, 41.915)
		λ	3.020	26.101	4.124	(1.890, 7.081)
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, season (wet)	0.011	p	0.664	0.644	0.648	(0.535, 0.747)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	9.344	27.123	6.529	(3.892, 20.636)
		λ	2.882	4.303	4.159	(1.957, 6.879)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.010	p	0.700	0.684	0.690	(0.570, 0.794)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	9.365	7.149	6.107	(3.240, 16.728)
		λ	2.882	4.303	4.159	(1.957, 6.879)

Riverine, pasture, sec. vegetation, urban, season (wet)	0.010	λ	1.994	3.383	3.280	(0.387, 6.569)
		p	0.656	0.645	0.649	(0.537, 0.757)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	18.529	>1000	10.478	(4.498, 113.624)
Riverine, pasture, eucalyptus, cane, sec. vegetation, urban	0.009	λ	2.805	3.728	3.452	(0.504, 6.551)
		p	0.697	0.661	0.667	(0.543, 0.788)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	10.264	469.73 1	9.296	(4.327, 72.310)
Cerrado, forest, riverine, agriculture, pasture, cane, sec. vegetation, urban, season (wet)	0.008	λ	3.150	>1000	4.433	(1.842, 7.251)
		p	0.679	0.666	0.672	(0.540, 0.772)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	8.303	8.453	6.188	(3.370, 17.161)
Riverine, pasture, sec. vegetation, season (wet)	0.007	λ	3.985	3.868	3.667	(0.168, 8.310)
		p	0.606	0.616	0.625	(0.468, 0.736)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	9.071	>1000	9.452	(3.881, 202.154)

Table 3. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Southern Crested-Caracara (*Caracara plancus*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 1201$ observations), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Cerrado, pasture, eucalyptus, cane	0.112	λ	0.573	0.790	0.726	(0.030, 1.874)
		p	0.782	0.719	0.767	(0.380, 0.966)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	5.734	>1000	4.719	(2.056, 160.782)
Cerrado, agriculture, pasture, eucalyptus, cane	0.102	λ	0.809	1.157	1.057	(0.229, 2.512)
		p	0.557	0.581	0.547	(0.337, 0.911)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	5.451	>1000	3.830	(1.743, 18.099)
Cerrado, riverine, agriculture, pasture, eucalyptus, cane	0.076	λ	1.069	1.367	1.297	(0.382, 2.643)
		p	0.450	0.518	0.466	(0.345, 0.891)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.976	21.709	3.311	(1.493, 14.335)
Cerrado, chaco, agriculture, pasture, eucalyptus, cane	0.056	λ	1.124	1.459	1.495	(0.308, 2.409)
		p	0.430	0.493	0.442	(0.334, 0.788)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.979	77.506	3.254	(1.510, 15.022)
Cerrado, riverine, pasture, eucalyptus, cane	0.054	λ	0.659	1.032	0.922	(0.058, 2.605)
		p	0.660	0.628	0.643	(0.345, 0.898)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	5.971	>1000	4.014	(1.563, 82.261)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane	0.053	λ	1.151	1.421	1.434	(0.455, 2.442)
		p	0.433	0.488	0.443	(0.344, 0.783)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.730	32.696	3.128	(1.504, 11.272)
Cerrado, pasture, cane	0.046	λ	0.674	0.922	0.768	(<0.000, 2.771)
		p	0.625	0.656	0.666	(0.333, 0.977)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)

		σ	6.290	>1000	4.844	(1.738, >1000)
		λ	0.664	0.962	0.886	(0.025, 2.066)
Cerrado, agriculture, pasture, cane	0.041	p	0.708	0.640	0.619	(0.364, 0.965)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	5.258	>1000	4.263	(1.803, 145.038)
		λ	0.810	1.171	1.136	(0.325, 2.173)
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, river level	0.040	p	0.616	0.579	0.573	(0.368, 0.848)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.744	>1000	3.238	(1.403, 15.079)
		λ	0.509	1.079	0.957	(0.091, 2.321)
Cerrado, chaco, agriculture, pasture, eucalyptus, cane, river level	0.038	p	0.726	0.639	0.652	(0.353, 0.937)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	6.960	26.850	3.414	(1.359, 68.757)
		λ	0.540	0.760	0.626	(0.005, 1.884)
Cerrado, pasture, eucalyptus	0.037	p	0.711	0.695	0.733	(0.375, 0.993)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	7.039	>1000	5.742	(1.996, 668.916)
		λ	0.865	1.275	1.193	(0.423, 2.328)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, river level	0.033	p	0.618	0.575	0.584	(0.356, 0.844)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.379	5.254	3.024	(1.475, 11.433)
		λ	0.671	1.061	0.903	(0.161, 2.400)
Cerrado, riverine, agriculture, pasture, cane	0.031	p	0.669	0.662	0.677	(0.341, 0.977)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	5.568	>1000	3.412	(1.511, 39.824)
		λ	0.896	1.128	0.885	(0.001, 2.829)
Cerrado, agriculture, pasture, eucalyptus	0.031	p	0.444	0.576	0.503	(0.316, 0.987)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	6.488	>1000	4.237	(1.627, >1000)
Pasture, eucalyptus, cane	0.029	λ	0.633	0.821	0.649	(<0.000, 2.236)

		p	0.622	0.659	0.666	(0.348, 0.995)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	6.748	>1000	5.060	(2.113, >1000)
Cerrado, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.021	λ	0.931	1.307	1.292	(0.397, 2.320)
		p	0.562	0.551	0.536	(0.359, 0.815)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Cerrado, riverine, agriculture, pasture, eucalyptus	0.019	σ	4.413	>1000	3.022	(1.418, 12.407)
		λ	0.686	1.167	0.952	(0.001, 3.326)
		p	0.459	0.586	0.529	(0.306, 0.998)
Cerrado, riverine, agriculture, pasture, eucalyptus	0.019	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	8.617	>1000	4.363	(1.237, >1000)
Cerrado, chaco, riverine, agriculture, pasture, cane	0.018	λ	0.786	1.071	0.995	(0.243, 2.077)
		p	0.698	0.624	0.638	(0.373, 0.910)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Cerrado, chaco, riverine, agriculture, pasture, cane	0.018	σ	4.288	>1000	3.466	(1.566, 19.982)
		λ	0.551	0.656	0.586	(<0.000, 1.685)
		p	0.647	0.694	0.727	(0.405, 0.990)
Cerrado, pasture	0.017	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	7.821	>1000	6.238	(2.162, >1000)
Cerrado, pasture	0.017	λ	0.531	0.596	0.612	(0.085, 1.025)
		p	0.983	0.978	0.986	(0.935, 1)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	0.015	σ	4.512	29.002	3.891	(1.584, 39.678)
		λ	0.705	1.081	0.967	(0.042, 2.739)
		p	0.699	0.633	0.659	(0.33, 0.953)
Cerrado, chaco, riverine, pasture, eucalyptus, cane	0.015	ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	5.220	>1000	3.603	(1.582, 212.932)
Agriculture, pasture, eucalyptus, cane	0.014	λ	0.537	0.843	0.744	(0.022, 2.056)
		p	0.771	0.689	0.752	(0.351, 0.975)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)

		σ	6.233	>1000	4.597	(1.802, 167.819)
		λ	0.641	1.136	1.078	(0.250, 2.305)
Cerrado, chaco, riverine, agriculture, pasture, cane, river level	0.013	p	0.642	0.623	0.639	(0.355, 0.931)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	6.161	62.109	3.523	(1.471, 26.139)
		λ	0.578	0.762	0.749	(0.268, 1.276)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.012	p	0.960	0.842	0.894	(0.572, 0.988)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.078	5.693	3.587	(1.258, 14.399)
		λ	1.511	1.440	1.471	(0.521, 2.268)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, river level	0.012	p	0.407	0.469	0.448	(0.370, 0.649)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	3.502	4.506	3.202	(1.503, 9.262)
		λ	0.498	0.654	0.622	(<0.000, 1.451)
Pasture, cane	0.012	p	0.742	0.733	0.799	(0.4, 0.996)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	7.392	>1000	5.549	(2.230, >1000)
		λ	0.865	1.292	1.172	(0.142, 2.640)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus	0.009	p	0.495	0.539	0.503	(0.340, 0.894)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	5.957	>1000	3.539	(1.613, 32.034)
		λ	1.190	1.332	1.348	(0.146, 2.511)
Riverine, agriculture, pasture, eucalyptus, cane	0.009	p	0.439	0.498	0.461	(0.325, 0.817)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.644	57.051	3.764	(1.629, 41.839)
		λ	0.952	1.537	1.545	(0.602, 2.506)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	0.008	p	0.419	0.475	0.433	(0.345, 0.736)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	6.329	6.248	3.021	(1.533, 8.209)
Cerrado, forest, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.007	λ	1.053	1.490	1.523	(0.514, 2.353)

		p	0.471	0.497	0.467	(0.357, 0.743)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.736	21.667	2.774	(1.460, 9.766)
Cerrado, chaco, riverine, pasture, eucalyptus, cane, river level	0.007	λ	0.992	1.299	1.196	(0.214, 2.677)
		p	0.507	0.543	0.500	(0.332, 0.831)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.945	11.024	3.552	(1.566, 22.009)
		λ	1.395	1.534	1.596	(0.470, 2.353)
Cerrado, forest, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.006	p	0.415	0.464	0.443	(0.351, 0.707)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	3.829	10.830	2.883	(1.407, 12.395)
		λ	1.092	1.166	1.100	(0.444, 2.168)
Cerrado, chaco, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.005	p	0.623	0.590	0.603	(0.370, 0.822)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	3.094	4.558	3.253	(1.504, 11.391)
		λ	1.315	1.473	1.465	(0.603, 2.402)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, river level	0.005	p	0.408	0.470	0.444	(0.350, 0.674)
		ϕ	<0.000	<0.000	<0.000	(<0.000, <0.000)
		σ	4.261	3.915	3.143	(1.457, 8.749)
		λ	1.315	1.473	1.465	(0.603, 2.402)

Table 4. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Savanna Hawk (*Buteogallus meridionalis*).

Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ observations), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Cerrado, forest, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.177	λ	3.808	3.882	3.806	(3.247, 4.834)
		p	0.286	0.302	0.300	(0.254, 0.357)
		ϕ	0.575	0.580	0.581	(0.534, 0.625)
Cerrado, chaco, riverine, agriculture, urban, cane, sec. vegetation, river level, season (wet)	0.097	λ	2.411	2.694	2.375	(1.333, 5.269)

		p	0.450	0.471	0.468	(0.235, 0.740)
		ϕ	0.576	0.568	0.572	(0.501, 0.615)
		λ	1.237	1.313	1.260	(1.048, 1.641)
Cerrado, chaco, agriculture, urban, cane, river level, season (wet)	0.086	p	0.888	0.856	0.885	(0.694, 0.926)
		ϕ	0.582	0.576	0.576	(0.523, 0.624)
		λ	1.609	1.957	1.719	(1.140, 4.075)
Cerrado, chaco, riverine, agriculture, urban, eucalyptus, cane, river level, season (wet)	0.075	p	0.687	0.639	0.657	(0.315, 0.863)
		ϕ	0.585	0.571	0.576	(0.51, 0.615)
		λ	1.572	1.982	1.705	(1.150, 3.746)
Cerrado, chaco, riverine, agriculture, urban, cane, river level, season (wet)	0.073	p	0.700	0.652	0.679	(0.353, 0.891)
		ϕ	0.586	0.573	0.578	(0.518, 0.621)
		λ	4.179	4.316	4.187	(2.277, 6.529)
Cerrado, chaco, riverine, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	0.065	p	0.259	0.289	0.264	(0.177, 0.466)
		ϕ	0.578	0.570	0.574	(0.507, 0.624)
		λ	2.447	2.426	2.382	(1.865, 2.933)
Cerrado, chaco, urban, cane, river level, season (wet)	0.045	p	0.474	0.494	0.493	(0.418, 0.587)
		ϕ	0.606	0.600	0.602	(0.550, 0.640)
		λ	1.248	1.541	1.368	(1.101, 2.615)
Cerrado, chaco, riverine, urban, cane, river level, season (wet)	0.045	p	0.932	0.837	0.892	(0.494, 0.983)
		ϕ	0.606	0.597	0.599	(0.543, 0.643)
		λ	1.623	1.998	1.706	(1.213, 3.681)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.044	p	0.677	0.646	0.663	(0.344, 0.889)
		ϕ	0.580	0.573	0.571	(0.522, 0.620)
		λ	2.251	2.731	2.345	(1.287, 5.083)
Cerrado, chaco, riverine, urban, cane, sec. vegetation, river level, season (wet)	0.036	p	0.517	0.526	0.531	(0.256, 0.807)
		ϕ	0.604	0.593	0.596	(0.539, 0.640)
		λ	1.144	1.216	1.152	(0.947, 1.635)
Cerrado, chaco, agriculture, urban, cane, sec. vegetation, river level, season (wet)	0.034	p	0.975	0.933	0.973	(0.708, 0.995)
		ϕ	0.588	0.572	0.576	(0.516, 0.614)
Cerrado, chaco, riverine, agriculture, eucalyptus, cane, sec. vegetation, river level, season (wet)	0.033	λ	1.829	1.850	1.801	(1.540, 2.161)

		p	0.556	0.566	0.570	(0.473, 0.637)
		ϕ	0.565	0.568	0.565	(0.523, 0.616)
		λ	2.340	2.889	2.457	(1.409, 5.784)
Cerrado, chaco, agriculture, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	0.032	p	0.469	0.451	0.451	(0.198, 0.738)
		ϕ	0.581	0.568	0.572	(0.511, 0.615)
		λ	1.394	1.905	1.566	(1.144, 3.830)
Cerrado, chaco, riverine, urban, eucalyptus, cane, sec. vegetation, river level, season (wet)	0.027	p	0.840	0.748	0.794	(0.407, 0.924)
		ϕ	0.604	0.598	0.603	(0.540, 0.643)
		λ	1.943	2.146	1.942	(1.237, 3.987)
Cerrado, chaco, riverine, agriculture, cane, river level, season (wet)	0.025	p	0.529	0.524	0.541	(0.265, 0.737)
		ϕ	0.573	0.571	0.571	(0.521, 0.623)
		λ	5.717	4.543	4.704	(2.219, 6.578)
Cerrado, chaco, riverine, agriculture, cane, sec. vegetation, river level, season (wet)	0.019	p	0.179	0.246	0.220	(0.160, 0.446)
		ϕ	0.572	0.561	0.563	(0.499, 0.616)
		λ	2.815	2.924	2.790	(1.709, 4.413)
Cerrado, chaco, agriculture, cane, river level, season (wet)	0.018	p	0.362	0.375	0.362	(0.235, 0.563)
		ϕ	0.571	0.567	0.565	(0.520, 0.620)
		λ	1.618	2.021	1.770	(1.192, 4.007)
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, sec. vegetation, urban, river level, season (wet)	0.018	p	0.674	0.634	0.657	(0.296, 0.863)
		ϕ	0.579	0.574	0.575	(0.519, 0.628)
		λ	1.760	2.189	1.930	(1.247, 4.175)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.014	p	0.630	0.586	0.597	(0.284, 0.844)
		ϕ	0.581	0.571	0.576	(0.508, 0.621)
		λ	2.813	3.189	2.921	(1.696, 5.407)
Cerrado, forest, chaco, riverine, agriculture, urban, cane, sec. vegetation, river level, season (wet)	0.013	p	0.382	0.401	0.386	(0.217, 0.711)
		ϕ	0.570	0.571	0.574	(0.510, 0.622)
		λ	1.484	1.945	1.662	(1.169, 3.669)
Cerrado, forest, chaco, riverine, pasture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.013	p	0.761	0.667	0.693	(0.387, 0.902)
		ϕ	0.593	0.580	0.583	(0.521, 0.633)
		λ	5.634	5.189	5.250	(2.265, 7.634)
Cerrado, chaco, riverine, agriculture, urban, sec. vegetation, river level, season (wet)	0.010	λ				

p	0.193	0.248	0.215	(0.151, 0.483)
ϕ	0.582	0.579	0.585	(0.521, 0.624)

Table 5. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Roadside Hawk (*Rupornis magnirostris*).

Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ observations), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Mean	Bootstrap Median	90% CI
Cane	0.213	λ	0.616	0.688	0.616	(0.462, 0.868)
		p	0.826	0.781	0.814	(0.602, 0.893)
		ϕ	0.559	0.538	0.549	(0.424, 0.611)
Riverine, cane	0.125	λ	0.537	0.558	0.552	(0.434, 0.685)
		p	0.970	0.923	0.964	(0.711, 0.993)
		ϕ	0.567	0.550	0.554	(0.456, 0.634)
Riverine, cane, sec. vegetation	0.110	λ	0.531	0.534	0.531	(0.421, 0.656)
		p	0.984	0.972	0.983	(0.917, 0.992)
		ϕ	0.567	0.558	0.565	(0.464, 0.647)
Riverine, pasture, cane	0.099	λ	0.509	0.521	0.520	(0.397, 0.623)
		p	0.983	0.971	0.982	(0.919, 0.99)
		ϕ	0.551	0.542	0.547	(0.447, 0.623)
Cane, sec. vegetation	0.078	λ	0.503	0.534	0.526	(0.438, 0.651)
		p	0.987	0.977	0.986	(0.941, 1)
		ϕ	0.551	0.560	0.563	(0.464, 0.632)
Riverine, pasture, cane, sec. vegetation	0.047	λ	0.640	0.772	0.642	(0.492, 0.955)
		p	0.794	0.751	0.781	(0.534, 0.878)
		ϕ	0.554	0.539	0.551	(0.419, 0.627)
Pasture, cane, sec. vegetation	0.046	λ	0.529	0.537	0.529	(0.401, 0.661)

		p	0.986	0.975	0.986	(0.944, 0.995)
		ϕ	0.566	0.560	0.565	(0.461, 0.639)
		λ	0.691	0.776	0.692	(0.517, 1.022)
Cerrado, riverine, pasture, cane	0.045	p	0.706	0.698	0.721	(0.505, 0.838)
		ϕ	0.538	0.530	0.540	(0.429, 0.610)
		λ	0.528	0.527	0.528	(0.400, 0.654)
Cerrado, pasture, cane, sec. vegetation	0.041	p	0.984	0.972	0.983	(0.924, 0.990)
		ϕ	0.564	0.552	0.558	(0.462, 0.633)
		λ	0.731	1.988	0.746	(0.511, 7.383)
Riverine	0.040	p	0.712	0.595	0.707	(0.070, 0.951)
		ϕ	0.567	0.555	0.559	(0.452, 0.640)
		λ	0.559	0.534	0.538	(0.438, 0.638)
Cerrado, riverine, cane, sec. vegetation	0.033	p	0.986	0.971	0.985	(0.900, 0.994)
		ϕ	0.584	0.557	0.561	(0.469, 0.631)
		λ	0.917	0.926	0.869	(0.592, 1.249)
Cerrado, riverine, pasture, cane, sec. vegetation	0.022	p	0.536	0.571	0.566	(0.449, 0.738)
		ϕ	0.539	0.535	0.541	(0.428, 0.621)
		λ	0.705	1.626	0.716	(0.463, 7.007)
Riverine, sec. vegetation	0.022	p	0.739	0.632	0.721	(0.075, 0.954)
		ϕ	0.566	0.551	0.557	(0.445, 0.636)
		λ	0.534	0.569	0.549	(0.419, 0.766)
Cerrado, chaco, riverine, cane, sec. vegetation	0.014	p	0.964	0.913	0.961	(0.617, 0.991)
		ϕ	0.562	0.545	0.549	(0.430, 0.636)
		λ	0.632	0.850	0.686	(0.485, 1.562)
Cerrado, chaco, riverine, pasture, cane	0.011	p	0.793	0.696	0.748	(0.291, 0.923)
		ϕ	0.547	0.531	0.540	(0.441, 0.612)
		λ	0.726	1.407	0.756	(0.523, 5.859)
Riverine, pasture, sec. vegetation	0.011	p	0.712	0.619	0.688	(0.084, 0.953)
		ϕ	0.561	0.549	0.555	(0.457, 0.629)
Cerrado, chaco, riverine, pasture, cane, sec. vegetation	0.010	λ	0.594	0.633	0.594	(0.447, 0.839)

			p	0.893	0.831	0.877	(0.593, 0.948)
			ϕ	0.568	0.537	0.543	(0.434, 0.618)
			λ	0.724	0.983	0.736	(0.526, 2.025)
Chaco, riverine, pasture, cane, sec. vegetation	0.009		p	0.692	0.632	0.687	(0.260, 0.901)
			ϕ	0.547	0.535	0.542	(0.423, 0.621)
			λ	0.658	0.839	0.673	(0.453, 1.798)
Cerrado, chaco, riverine, agriculture, pasture, cane	0.008		p	0.692	0.658	0.693	(0.219, 0.908)
			ϕ	0.506	0.496	0.501	(0.379, 0.594)
			λ	1.465	1.399	1.397	(0.573, 2.080)
Cerrado, riverine, agriculture, pasture, cane, sec. vegetation	0.008		p	0.316	0.370	0.337	(0.212, 0.669)
			ϕ	0.515	0.498	0.509	(0.365, 0.590)
			λ	0.646	0.739	0.644	(0.486, 1.014)
Cerrado, chaco, pasture, cane, sec. vegetation	0.008		p	0.776	0.745	0.781	(0.488, 0.938)
			ϕ	0.548	0.533	0.540	(0.414, 0.625)

Table 6. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for White-tailed Hawk (*Geranoaetus albicaudatus*). Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ observations), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Urban	0.143	λ	8.923	6.865	7.244	(1.281, 9.756)
		p	0.061	0.105	0.075	(0.052, 0.312)
		ϕ	0.780	0.763	0.770	(0.667, 0.825)
Urban, river level, season (wet)	0.088	λ	0.535	>1000	0.524	(0.355, 0.719)
		p	1.000	0.976	1.000	(0.873, 1)
		ϕ	0.777	0.760	0.765	(0.682, 0.817)
Urban, season (wet)	0.088	λ	7.506	5.510	6.295	(0.629, 9.084)

		p	0.072	0.185	0.087	(0.054, 0.693)
		ϕ	0.781	0.765	0.773	(0.689, 0.826)
		λ	0.621	0.637	0.627	(0.432, 0.88)
River level, season (wet)	0.087	p	0.951	0.939	0.945	(0.900, 0.972)
		ϕ	0.796	0.785	0.791	(0.731, 0.834)
		λ	6.634	5.790	5.319	(0.797, 8.678)
Urban, river level	0.086	p	0.081	0.148	0.102	(0.072, 0.600)
		ϕ	0.776	0.766	0.772	(0.697, 0.826)
		λ	7.955	7.220	7.510	(0.915, 11.021)
Season (wet)	0.085	p	0.078	0.137	0.081	(0.055, 0.557)
		ϕ	0.811	0.802	0.804	(0.737, 0.856)
		λ	0.527	>1000	0.525	(0.342, 0.711)
Cane, urban, season (wet)	0.055	p	1.000	0.992	1.000	(0.945, 1)
		ϕ	0.775	0.761	0.767	(0.679, 0.823)
		λ	3.730	>1000	3.652	(0.805, 8.678)
Cane, river level, season (wet)	0.046	p	0.159	0.200	0.155	(0.07, 0.674)
		ϕ	0.800	0.784	0.790	(0.707, 0.837)
		λ	6.151	>1000	5.129	(2.084, 9.121)
Cane, urban, river level	0.042	p	0.085	0.142	0.102	(0.071, 0.417)
		ϕ	0.769	0.760	0.761	(0.691, 0.824)
		λ	0.517	>1000	0.520	(0.359, 0.746)
Cane, urban, river level, season (wet)	0.041	p	1.000	0.999	1.000	(1, 1)
		ϕ	0.769	0.761	0.766	(0.688, 0.819)
		λ	2.528	>1000	3.139	(0.646, 8.890)
Sec. vegetation, urban, river level, season (wet)	0.037	p	0.213	0.258	0.170	(0.073, 0.771)
		ϕ	0.778	0.756	0.766	(0.666, 0.829)
		λ	0.532	>1000	0.533	(0.356, 0.904)
Cane, sec. vegetation, urban, season (wet)	0.029	p	1.000	0.980	1.000	(0.913, 1)
		ϕ	0.776	0.763	0.767	(0.679, 0.827)
Cane, sec. vegetation, river level, season (wet)	0.024	λ	6.974	>1000	4.854	(0.573, 10.201)

		p	0.086	0.261	0.129	(0.072, 0.870)
		ϕ	0.801	0.788	0.793	(0.710, 0.841)
		λ	0.514	>1000	0.556	(0.330, 2.871)
Cane, sec. vegetation, urban, river level, season (wet)	0.020	p	0.997	0.913	0.993	(0.583, 1)
		ϕ	0.766	0.747	0.758	(0.659, 0.815)
		λ	5.807	>1000	4.986	(0.693, >1000)
Cane, sec. vegetation, urban, river level	0.019	p	0.091	0.170	0.112	(0.072, 0.545)
		ϕ	0.770	0.755	0.762	(0.663, 0.821)
		λ	0.510	>1000	0.538	(0.345, >1000)
Forest, cane, urban, river level, season (wet)	0.019	p	0.987	0.947	0.958	(0.846, 1)
		ϕ	0.762	0.750	0.756	(0.653, 0.820)
		λ	4.778	>1000	3.847	(0.658, 33.972)
Forest, sec. vegetation, urban, river level, season (wet)	0.017	p	0.110	0.251	0.143	(0.085, 0.822)
		ϕ	0.769	0.753	0.759	(0.652, 0.818)
		λ	0.590	>1000	0.611	(0.405, 1.918)
Forest, cane, sec. vegetation, river level, season (wet)	0.016	p	0.959	0.951	0.953	(0.892, 1)
		ϕ	0.785	0.773	0.782	(0.691, 0.828)
		λ	0.597	>1000	0.604	(0.378, >1000)
Forest, cane, sec. vegetation, urban, season (wet)	0.014	p	0.995	0.982	0.995	(0.936, 1)
		ϕ	0.786	0.772	0.775	(0.689, 0.836)
		λ	0.520	>1000	0.529	(0.351, >1000)
Forest, cane, sec. vegetation, urban, river level, season (wet)	0.010	p	1.000	0.979	1.000	(0.899, 1)
		ϕ	0.767	0.750	0.753	(0.670, 0.817)
		λ	4.382	>1000	3.872	(0.716, >1000)
Forest, cane, sec. vegetation, urban, river level	0.009	p	0.116	0.218	0.149	(0.079, 0.754)
		ϕ	0.759	0.748	0.756	(0.667, 0.816)
		λ	0.490	>1000	0.542	(0.346, >1000)
Forest, riverine, sec. vegetation, urban, river level, season (wet)	0.009	p	0.995	0.984	0.995	(0.939, 1)
		ϕ	0.754	0.738	0.747	(0.639, 0.819)
Riverine, cane, sec. vegetation, urban, river level, season (wet)	0.008	λ	0.508	>1000	0.532	(0.325, >1000)

Forest, riverine, cane, urban, river level, season (wet)	0.007	p	0.995	0.982	0.995	(0.940, 1)
		ϕ	0.763	0.746	0.756	(0.636, 0.825)
		λ	4.786	>1000	3.999	(0.672, >1000)
		p	0.098	0.196	0.136	(0.080, 0.667)
		ϕ	0.744	0.734	0.735	(0.640, 0.819)

Table 7. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for American Kestrel (*Falco sparverius*). Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ observations), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
eucalyptus, cane, urban, season (wet)	0.119	λ	1.409	1.962	1.647	(0.969, 3.104)
		p	0.584	0.530	0.545	(0.281, 0.768)
		ϕ	0.707	0.696	0.695	(0.636, 0.751)
Agriculture, eucalyptus, cane, urban, season (wet)	0.113	λ	1.527	1.670	1.563	(0.849, 2.768)
		p	0.537	0.539	0.536	(0.341, 0.783)
		ϕ	0.697	0.683	0.687	(0.617, 0.741)
eucalyptus, urban, season (wet)	0.102	λ	1.363	1.574	1.367	(0.899, 3.312)
		p	0.573	0.551	0.560	(0.260, 0.787)
		ϕ	0.713	0.701	0.703	(0.635, 0.751)
Agriculture, eucalyptus, urban, season (wet)	0.082	λ	1.283	1.504	1.400	(0.882, 2.511)
		p	0.581	0.548	0.549	(0.293, 0.781)
		ϕ	0.698	0.683	0.688	(0.618, 0.740)
Riverine, agriculture, eucalyptus, cane, urban, season (wet)	0.067	λ	1.504	1.752	1.622	(0.965, 3.014)
		p	0.546	0.514	0.517	(0.270, 0.724)
		ϕ	0.694	0.675	0.677	(0.610, 0.736)
Riverine, agriculture, eucalyptus, urban, season (wet)	0.058	λ	1.289	1.476	1.401	(0.925, 2.477)

		p	0.583	0.547	0.541	(0.321, 0.763)
		ϕ	0.694	0.685	0.690	(0.620, 0.742)
		λ	1.526	10.926	1.506	(0.980, 2.746)
Riverine, eucalyptus, cane, urban, season (wet)	0.056	p	0.561	0.555	0.557	(0.366, 0.743)
		ϕ	0.711	0.696	0.700	(0.630, 0.748)
		λ	1.550	2.559	1.630	(1.067, 2.967)
Cane, urban, season (wet)	0.044	p	0.569	0.544	0.540	(0.371, 0.752)
		ϕ	0.719	0.708	0.707	(0.662, 0.755)
		λ	1.374	1.717	1.439	(0.980, 3.479)
Urban, season (wet)	0.043	p	0.590	0.542	0.553	(0.254, 0.787)
		ϕ	0.720	0.710	0.709	(0.665, 0.762)
		λ	1.553	1.706	1.531	(0.976, 2.871)
Riverine, agriculture, cane, urban, season (wet)	0.042	p	0.544	0.532	0.544	(0.330, 0.692)
		ϕ	0.699	0.684	0.688	(0.620, 0.743)
		λ	1.306	1.590	1.380	(0.881, 3.338)
eucalyptus, season (wet)	0.031	p	0.596	0.556	0.567	(0.273, 0.814)
		ϕ	0.718	0.704	0.706	(0.642, 0.753)
		λ	1.314	14.196	1.384	(0.888, 8.291)
Forest, riverine, agriculture, eucalyptus, urban, season (wet)	0.026	p	0.591	0.575	0.581	(0.356, 0.772)
		ϕ	0.697	0.683	0.689	(0.600, 0.744)
		λ	1.348	171.184	1.646	(1.032, 36.892)
Forest, riverine, agriculture, eucalyptus, cane, urban, season (wet)	0.025	p	0.595	0.555	0.567	(0.371, 0.738)
		ϕ	0.696	0.686	0.687	(0.632, 0.739)
		λ	1.659	>1000	1.691	(1.044, 12.776)
Forest, riverine, eucalyptus, cane, urban, season (wet)	0.025	p	0.542	0.544	0.546	(0.357, 0.729)
		ϕ	0.715	0.699	0.704	(0.640, 0.745)
		λ	1.450	5.006	1.550	(1.019, 2.989)
Riverine, agriculture, eucalyptus, cane, urban, river level, season (wet)	0.025	p	0.565	0.531	0.540	(0.347, 0.69)
		ϕ	0.694	0.678	0.678	(0.620, 0.738)
Agriculture, eucalyptus, cane, season (wet)	0.022	λ	1.436	1.526	1.432	(0.906, 2.312)

		p	0.558	0.558	0.540	(0.351, 0.791)
		ϕ	0.707	0.691	0.695	(0.624, 0.746)
Agriculture, cane, urban, season (wet)	0.020	λ	2.375	1.910	1.701	(1.068, 3.281)
		p	0.366	0.489	0.494	(0.302, 0.689)
		ϕ	0.702	0.689	0.691	(0.623, 0.741)
Riverine, agriculture, eucalyptus, cane, season (wet)	0.019	λ	1.266	1.604	1.494	(0.931, 2.697)
		p	0.606	0.549	0.555	(0.297, 0.749)
		ϕ	0.700	0.687	0.690	(0.623, 0.746)
Forest, riverine, agriculture, cane, urban, season (wet)	0.017	λ	1.573	>1000	1.591	(1.070, 5.039)
		p	0.554	0.555	0.546	(0.404, 0.713)
		ϕ	0.702	0.687	0.692	(0.612, 0.744)
Forest, riverine, agriculture, eucalyptus, cane, urban, river level, season (wet)	0.012	λ	1.601	>1000	1.772	(1.126, 24.375)
		p	0.546	0.536	0.539	(0.342, 0.704)
		ϕ	0.701	0.683	0.684	(0.608, 0.744)
Forest, riverine, agriculture, eucalyptus, urban, river level, season (wet)	0.010	λ	1.376	8.720	1.552	(1.026, 12.998)
		p	0.578	0.561	0.568	(0.382, 0.749)
		ϕ	0.701	0.689	0.688	(0.631, 0.745)
Forest, riverine, eucalyptus, cane, urban, river level, season (wet)	0.009	λ	1.655	146.702	1.763	(1.121, 7.774)
		p	0.538	0.538	0.538	(0.346, 0.705)
		ϕ	0.714	0.696	0.699	(0.629, 0.749)
Forest, riverine, agriculture, eucalyptus, cane, season (wet)	0.008	λ	1.280	15.894	1.459	(0.915, 5.591)
		p	0.633	0.579	0.584	(0.367, 0.784)
		ϕ	0.711	0.688	0.686	(0.626, 0.746)
Forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, season (wet)	0.007	λ	1.308	>1000	1.630	(1.006, 12.865)
		p	0.605	0.565	0.571	(0.412, 0.730)
		ϕ	0.697	0.684	0.687	(0.619, 0.736)
Forest, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.007	λ	1.476	12.335	1.823	(1.103, 13.814)
		p	0.596	0.553	0.566	(0.355, 0.742)
		ϕ	0.701	0.687	0.691	(0.617, 0.745)
Forest, riverine, agriculture, cane, urban, river level, season (wet)	0.007	λ	1.582	3.380	1.643	(1.160, 5.098)

Forest, riverine, agriculture, eucalyptus, cane, sec. vegetation, urban, river level, season (wet)	0.004	p	0.556	0.560	0.563	(0.432, 0.680)
		ϕ	0.704	0.692	0.692	(0.628, 0.744)
		λ	1.460	>1000	1.662	(1.088, 52.234)
		p	0.583	0.554	0.553	(0.378, 0.738)
		ϕ	0.696	0.686	0.687	(0.630, 0.742)

Table 8. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Aplomado Falcon (*Falco femoralis*). Models based on the binomial–zero-inflated Poisson mixture ($n = 1201$ observations), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Cerrado, chaco, riverine, agriculture, pasture, cane	0.274	λ	9.653	>1000	9.413	(2.172, 29.639)
		p	0.269	0.308	0.278	(0.171, 0.561)
		ϕ	0.817	0.801	0.810	(0.704, 0.878)
Chaco, riverine, agriculture, pasture, cane	0.081	λ	2.608	>1000	2.361	(0.645, >1000)
		p	0.139	0.221	0.167	(0.124, 0.624)
		ϕ	0.776	0.779	0.788	(0.674, 0.867)
Cerrado, urban, chaco, riverine, agriculture, pasture	0.072	λ	1.877	>1000	3.315	(0.740, >1000)
		p	0.270	0.313	0.228	(0.145, 0.732)
		ϕ	0.787	0.786	0.797	(0.625, 0.881)
Cerrado, chaco, riverine, pasture, cane	0.066	λ	2.433	>1000	2.072	(0.884, 3.441)
		p	0.148	0.208	0.174	(0.124, 0.445)
		ϕ	0.773	0.753	0.757	(0.611, 0.853)
Cerrado, chaco, agriculture, pasture, cane	0.053	λ	1.795	>1000	2.225	(0.676, 46.549)
		p	0.422	0.411	0.418	(0.165, 0.778)

		ϕ	0.847	0.834	0.851	(0.727, 0.892)
		λ	6.640	>1000	11.140	(1.747, >1000)
Cerrado, chaco, riverine, agriculture, pasture, cane, sec. vegetation	0.049	p	0.175	0.271	0.213	(0.135, 0.622)
		ϕ	0.824	0.804	0.819	(0.687, 0.882)
		λ	25.840	>1000	38.220	(3.432, >1000)
Cerrado, riverine, agriculture, pasture, cane, forest, sec. vegetation	0.039	p	0.481	0.402	0.382	(0.162, 0.740)
		ϕ	0.840	0.818	0.830	(0.705, 0.89)
		λ	2.393	>1000	2.314	(0.667, >1000)
Cerrado, chaco, riverine, agriculture, cane	0.038	p	0.168	0.240	0.185	(0.132, 0.615)
		ϕ	0.792	0.782	0.796	(0.654, 0.87)
		λ	3.321	>1000	2.981	(0.65, 354.291)
Cerrado, riverine, agriculture, pasture, cane	0.037	p	0.168	0.331	0.222	(0.140, 0.831)
		ϕ	0.829	0.804	0.815	(0.687, 0.893)
		λ	2.764	>1000	2.662	(0.693, >1000)
Chaco, riverine, agriculture, pasture, cane, sec. vegetation	0.030	p	0.148	0.222	0.175	(0.132, 0.585)
		ϕ	0.794	0.763	0.786	(0.577, 0.872)
		λ	7.137	>1000	10.313	(1.044, >1000)
Cerrado, chaco, agriculture, pasture, cane, sec. vegetation	0.027	p	0.484	0.418	0.378	(0.149, 0.803)
		ϕ	0.866	0.839	0.853	(0.723, 0.900)
		λ	2.588	>1000	3.718	(0.621, >1000)
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation	0.025	p	0.198	0.274	0.201	(0.126, 0.645)
		ϕ	0.808	0.802	0.816	(0.691, 0.879)
		λ	3.287	>1000	7.900	(1.191, >1000)
Cerrado, chaco, riverine, agriculture, pasture, forest, cane, sec. vegetation	0.021	p	0.221	0.285	0.230	(0.145, 0.586)
		ϕ	0.823	0.805	0.820	(0.678, 0.886)
		λ	0.922	>1000	1.088	(0.599, 266.591)
Cerrado, chaco, riverine, agriculture, pasture, forest, cane, season (wet)	0.021	p	0.442	0.416	0.432	(0.203, 0.701)
		ϕ	0.804	0.782	0.793	(0.662, 0.875)
		λ	2.816	>1000	2.979	(0.711, >1000)
Cerrado, chaco, riverine, pasture, cane, sec. vegetation	0.021	p	0.143	0.228	0.175	(0.121, 0.545)

		ϕ	0.794	0.765	0.789	(0.580, 0.868)
		λ	1.439	>1000	5.118	(0.976, >1000)
Cerrado, chaco, riverine, agriculture, pasture, cane, forest, sec. vegetation	0.019	p	0.305	0.334	0.285	(0.159, 0.696)
		ϕ	0.818	0.796	0.809	(0.672, 0.876)
		λ	10.244	>1000	14.260	(1.847, >1000)
Cerrado, chaco, riverine, agriculture, pasture, cane, season (wet), sec. vegetation	0.017	p	0.201	0.302	0.236	(0.149, 0.662)
		ϕ	0.832	0.804	0.822	(0.671, 0.888)
		λ	2.752	>1000	2.854	(1.163, >1000)
Cerrado, chaco, riverine, agriculture, cane, sec. vegetation	0.014	p	0.148	0.211	0.173	(0.131, 0.467)
		ϕ	0.798	0.798	0.808	(0.682, 0.879)
		λ	3.257	>1000	3.431	(0.927, >1000)
Cerrado, riverine, agriculture, pasture, cane, sec. vegetation	0.013	p	0.169	0.280	0.197	(0.130, 0.653)
		ϕ	0.827	0.820	0.830	(0.717, 0.891)
		λ	98.253	>1000	171.973	(3.153, >1000)
Cerrado, riverine, agriculture, pasture, forest, cane, season (wet), sec. vegetation	0.011	p	0.369	0.364	0.298	(0.164, 0.741)
		ϕ	0.859	0.835	0.842	(0.756, 0.890)
		λ	2.862	>1000	27.238	(0.944, >1000)
Cerrado, chaco, agriculture, pasture, cane, forest, sec. vegetation	0.010	p	0.558	0.452	0.432	(0.159, 0.833)
		ϕ	0.855	0.838	0.853	(0.717, 0.898)
		λ	1.449	>1000	1.936	(1.054, >1000)
Cerrado, forest, chaco, riverine, agriculture, pasture, cane, season (wet), sec. vegetation	0.009	p	0.309	0.351	0.328	(0.202, 0.589)
		ϕ	0.819	0.809	0.816	(0.701, 0.876)
		λ	1.035	>1000	1.089	(0.690, >1000)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, season (wet)	0.008	p	0.328	0.357	0.334	(0.195, 0.621)
		ϕ	0.767	0.764	0.775	(0.634, 0.853)
		λ	2.165	>1000	47.731	(0.903, >1000)
Chaco, riverine, agriculture, pasture, cane, forest, sec. vegetation	0.008	p	0.165	0.236	0.175	(0.128, 0.665)
		ϕ	0.778	0.789	0.810	(0.618, 0.870)
		λ	2.048	>1000	3.297	(1.017, >1000)
Cerrado, chaco, riverine, agriculture, pasture, forest, sec. vegetation	0.008	p	0.227	0.272	0.223	(0.144, 0.573)

		ϕ	0.807	0.805	0.816	(0.696, 0.874)
		λ	>1000	>1000	>1000	(>1000, >1000)
Cerrado, forest, chaco, riverine, agriculture, pasture, eucalyptus, cane, sec. vegetation	0.007	p	0.310	0.342	0.328	(0.166, 0.654)
		ϕ	0.850	0.846	0.850	(0.782, 0.894)
		λ	7.259	>1000	13.891	(2.103, >1000)
Cerrado, chaco, riverine, agriculture, pasture, eucalyptus, cane, season (wet), sec. vegetation	0.007	p	0.249	0.328	0.281	(0.166, 0.652)
		ϕ	0.813	0.785	0.795	(0.666, 0.872)
		λ	1.520	>1000	2.654	(1.133, >1000)
Cerrado, chaco, riverine, pasture, cane, forest, sec. vegetation	0.007	p	0.248	0.245	0.210	(0.143, 0.509)
		ϕ	0.791	0.782	0.790	(0.661, 0.864)
		λ	2.262	>1000	2.415	(1.193, >1000)
Chaco, riverine, agriculture, pasture, forest, cane, season (wet), sec. vegetation	0.005	p	0.156	0.206	0.176	(0.135, 0.413)
		ϕ	0.778	0.782	0.789	(0.658, 0.866)
		λ	2.836	>1000	3.636	(1.047, >1000)
Cerrado, chaco, riverine, agriculture, cane, forest, sec. vegetation	0.005	p	0.150	0.212	0.177	(0.133, 0.461)
		ϕ	0.804	0.800	0.814	(0.692, 0.872)

Table 9. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Snail Kite (*Rosthramus sociabilis*), with 90% non-parametric bootstrap confidence intervals. Models based on the binomial–zero-inflated negative binomial mixture ($n = 195$ observations), where λ is the rate parameter of the NB distribution, p = detection probability, ϕ = zero-inflation probability and σ is the overdispersion parameter (where $\sigma = 0$ is the Poisson case).

Model (abundance covariates)	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
		λ	3.552	3.158	3.179	(1.430, 4.673)
		p	0.343	0.424	0.392	(0.296, 0.662)
Cerrado, riverine, pasture, river level	0.239	ϕ	0.340	0.315	0.326	(0.140, 0.477)
		σ	0.138	4.577	0.140	(0.001, 0.645)
		λ	3.030	2.868	2.875	(1.233, 4.584)
Cerrado, pasture, river level	0.189	p	0.391	0.452	0.408	(0.322, 0.703)

		ϕ	0.275	0.276	0.283	(0.080, 0.451)
		σ	0.267	0.267	0.164	(<0.000, 0.755)
Cerrado, sec. vegetation, riverine, pasture, river level	0.122	λ	3.526	140.357	3.165	(1.292, 5.627)
		p	0.346	0.460	0.410	(0.291, 0.808)
		ϕ	0.333	0.314	0.334	(0.110, 0.478)
		σ	0.162	0.238	0.124	(<0.000, 0.696)
		λ	2.726	>1000	3.361	(1.115, >1000)
Cerrado, riverine, agriculture, pasture, sec. vegetation, river level	0.074	p	0.431	0.466	0.409	(0.292, 0.806)
		ϕ	0.291	0.306	0.318	(0.102, 0.485)
		σ	0.211	0.426	0.182	(0.001, 0.702)
		λ	3.069	16.754	3.008	(1.459, 5.211)
Cerrado, sec. vegetation, pasture, river level	0.062	p	0.361	0.440	0.421	(0.293, 0.660)
		ϕ	0.266	0.282	0.290	(0.063, 0.436)
		σ	0.273	0.283	0.146	(<0.000, 0.846)
		λ	3.356	>1000	3.517	(1.447, 18.342)
Cerrado, forest, riverine, agriculture, pasture, river level	0.048	p	0.348	0.426	0.387	(0.296, 0.719)
		ϕ	0.000	0.074	0.000	(<0.000, 0.436)
		σ	0.177	0.335	0.159	(0.003, 0.700)
		λ	2.868	136.670	3.347	(1.813, 5.978)
Cerrado, riverine, pasture, agriculture, river level	0.030	p	0.339	0.385	0.365	(0.260, 0.625)
		ϕ	0.234	0.303	0.311	(0.103, 0.470)
		σ	0.486	0.477	0.120	(0.001, 0.766)
		λ	2.690	>1000	3.383	(1.157, >1000)
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, forest, river level	0.030	p	0.333	0.471	0.403	(0.283, 0.902)
		ϕ	0.225	0.298	0.302	(0.096, 0.469)
		σ	0.258	0.174	0.072	(<0.000, 0.641)
		λ	3.898	>1000	3.824	(1.394, >1000)
Cerrado, riverine, agriculture, pasture, sec. vegetation, river level, forest	0.029	p	0.302	0.427	0.382	(0.279, 0.829)
		ϕ	0.316	0.312	0.318	(0.111, 0.466)
		σ	0.181	14.685	0.137	(0.001, 0.744)
		λ	3.898	>1000	3.824	(1.394, >1000)

Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, river level	0.024	λ	2.857	>1000	3.002	(0.990, >1000)
		p	0.335	0.535	0.492	(0.268, 0.940)
		ϕ	0.225	0.288	0.293	(0.093, 0.480)
		σ	0.505	0.369	0.138	(<0.000, 0.663)
Cerrado, forest, riverine, pasture, sec. vegetation, river level	0.024	λ	3.978	202.893	3.857	(1.56, 16.607)
		p	0.328	0.432	0.378	(0.286, 0.809)
		ϕ	0.339	0.332	0.339	(0.168, 0.468)
		σ	0.056	0.183	0.100	(<0.000, 0.597)
Cerrado, chaco, riverine, agriculture, pasture, river level, forest	0.024	λ	1.808	183.532	2.901	(1.317, 43.184)
		p	0.451	0.442	0.407	(0.285, 0.749)
		ϕ	0.121	0.277	0.289	(0.083, 0.435)
		σ	0.514	0.200	0.102	(0.001, 0.581)
Cerrado, chaco, riverine, agriculture, pasture, sec. vegetation, river level, season (wet)	0.023	λ	3.522	>1000	3.265	(1.082, >1000)
		p	0.305	0.566	0.518	(0.265, 0.929)
		ϕ	0.289	0.286	0.301	(0.092, 0.464)
		σ	0.211	0.207	0.092	(<0.000, 0.500)
Cerrado, chaco, riverine, pasture, sec. vegetation, river level, forest	0.023	λ	2.591	9.812	3.313	(1.300, 19.439)
		p	0.343	0.450	0.396	(0.283, 0.835)
		ϕ	0.204	0.302	0.312	(0.107, 0.480)
		σ	0.448	>1000	0.124	(<0.000, 0.567)
Cerrado, forest, agriculture, pasture, sec. vegetation, river level	0.013	λ	3.308	>1000	4.888	(1.640, >1000)
		p	0.380	0.442	0.409	(0.293, 0.699)
		ϕ	0.272	0.321	0.318	(0.121, 0.504)
		σ	0.234	3.167	0.184	(0.002, 0.812)
Riverine, pasture, river level	0.011	λ	2.640	2.670	2.598	(1.167, 4.464)
		p	0.408	0.459	0.429	(0.308, 0.721)
		ϕ	0.273	0.278	0.298	(<0.000, 0.467)
		σ	0.589	1.245	0.402	(0.004, 1.973)
Cerrado, forest, chaco, riverine, agriculture, pasture, sec. vegetation, river level, season (wet)	0.009	λ	2.609	>1000	3.364	(1.179, >1000)
		p	0.338	0.495	0.397	(0.261, 0.901)

Cerrado, chaco, riverine, pasture, sec. vegetation, forest, river level, season (wet)	0.009	ϕ	0.239	0.301	0.305	(0.102, 0.484)
		σ	0.261	0.147	0.067	(<0.000, 0.498)
		λ	3.113	>1000	3.271	(1.028, 55.309)
		p	0.322	0.526	0.443	(0.281, 0.877)
		ϕ	0.297	0.292	0.301	(0.060, 0.467)
		σ	0.190	23.827	0.107	(<0.000, 0.675)
Cerrado, chaco, riverine, agriculture, pasture, forest, river level, season (wet)	0.008	λ	1.529	>1000	2.877	(1.126, 31.979)
		p	0.531	0.482	0.417	(0.292, 0.920)
		ϕ	0.162	0.280	0.292	(0.095, 0.433)
		σ	0.531	0.148	0.106	(0.002, 0.483)
Cerrado, sec. vegetation, pasture, agriculture, river level	0.008	λ	3.818	>1000	3.370	(1.350, >1000)
		p	0.261	0.404	0.378	(0.265, 0.645)
		ϕ	0.236	0.269	0.278	(0.033, 0.455)
		σ	0.335	>1000	0.178	(<0.000, 0.961)

Table 10. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Black-collared Hawk (*Busarellus nigricolis*).

Models based on the binomial–zero-inflated Poisson mixture ($n = 195$ observations), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariates	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Forest, chaco, pasture, season (wet)	0.169	λ	1.021	1.127	1.032	(0.688,1.804)
		p	0.939	0.913	0.936	(0.846,0.953)
		ϕ	0.538	0.508	0.517	(0.333,0.661)
Cerrado, forest, chaco, pasture, season (wet)	0.119	λ	1.015	1.067	1.019	(0.660,1.57)
		p	0.933	0.913	0.928	(0.833,0.949)
		ϕ	0.531	0.493	0.495	(0.332,0.635)
Forest, chaco, pasture, sec.vegetation, season (wet)	0.084	λ	0.956	>1000	1.001	(0.640,>1000)

		p	0.932	0.917	0.932	(0.851,0.952)
		ϕ	0.507	0.478	0.482	(0.312,0.61)
		λ	0.947	>1000	1.037	(0.660,>1000)
Cerrado, forest, chaco, pasture, sec.vegetation, season (wet)	0.082	p	0.934	0.922	0.934	(0.852,0.952)
		ϕ	0.496	0.479	0.488	(0.338,0.594)
		λ	0.910	>1000	2.004	(0.758,>1000)
Forest, chaco, pasture, sec.vegetation, agriculture, season (wet)	0.044	p	0.935	0.917	0.935	(0.822,0.957)
		ϕ	0.477	0.485	0.483	(0.362,0.620)
		λ	0.996	1.859	0.984	(0.622,1.537)
Cerrado, forest, chaco, pasture	0.038	p	0.921	0.906	0.923	(0.841,0.948)
		ϕ	0.541	0.504	0.516	(0.339,0.635)
		λ	1.810	2.934	2.204	(0.788,6.740)
Forest, pasture, season (wet)	0.036	p	0.573	0.531	0.539	(0.181,0.930)
		ϕ	0.543	0.511	0.526	(0.333,0.680)
		λ	0.996	1.015	0.982	(0.668,1.526)
Forest, chaco, pasture	0.035	p	0.929	0.915	0.926	(0.849,0.949)
		ϕ	0.552	0.523	0.536	(0.352,0.662)
		λ	1.186	1.184	1.136	(0.709,1.797)
Chaco, pasture, season (wet)	0.034	p	0.943	0.934	0.939	(0.896,0.948)
		ϕ	0.590	0.543	0.552	(0.353,0.704)
		λ	1.052	>1000	1.094	(0.730,>1000)
Cerrado, forest, chaco, sec.vegetation, season (wet)	0.029	p	0.944	0.921	0.941	(0.843,0.960)
		ϕ	0.550	0.530	0.540	(0.399,0.640)
		λ	>1000	>1000	>1000	(1.062,>1000)
Cerrado, forest, chaco, pasture, sec.vegetation, urban, season (wet)	0.028	p	0.937	0.917	0.934	(0.847,0.950)
		ϕ	0.491	0.477	0.483	(0.333,0.606)
		λ	1.193	1.251	1.209	(0.790,1.784)
Forest, chaco, season (wet)	0.028	p	0.940	0.921	0.940	(0.823,0.957)
		ϕ	0.607	0.583	0.591	(0.455,0.692)
Cerrado, forest, pasture, sec.vegetation, season (wet)	0.024	λ	0.966	>1000	1.016	(0.681,3.342)

		p	0.934	0.907	0.935	(0.770,0.950)
		ϕ	0.514	0.494	0.501	(0.329,0.626)
		λ	1.051	1.209	1.087	(0.650,2.342)
Cerrado, forest, pasture, season (wet)	0.024	p	0.936	0.893	0.927	(0.674,0.960)
		ϕ	0.554	0.500	0.505	(0.312,0.657)
		λ	0.873	351.939	0.875	(0.551,1.529)
Cerrado, forest, chaco, pasture, sec.vegetation	0.024	p	0.861	0.837	0.849	(0.750,0.899)
		ϕ	0.432	0.411	0.415	(0.257,0.563)
		λ	0.843	>1000	0.986	(0.633,>1000)
Cerrado, forest, chaco, pasture, sec.vegetation, agriculture, season (wet)	0.023	p	0.930	0.923	0.931	(0.853,0.952)
		ϕ	0.437	0.458	0.449	(0.320,0.607)
		λ	0.919	>1000	1.146	(0.715,>1000)
Cerrado, forest, chaco, pasture, urban, river level, season (wet)	0.023	p	0.936	0.923	0.935	(0.856,0.954)
		ϕ	0.496	0.477	0.479	(0.311,0.617)
		λ	0.921	>1000	0.985	(0.636,2.256)
Cerrado, forest, chaco, pasture, sec.vegetation, river level, season (wet)	0.022	p	0.932	0.904	0.926	(0.777,0.957)
		ϕ	0.485	0.443	0.452	(0.296,0.594)
		λ	4.615	>1000	10.014	(0.619,>1000)
Cerrado, forest, chaco, pasture, urban, agriculture, season (wet)	0.02	p	0.932	0.917	0.931	(0.842,0.951)
		ϕ	0.472	0.449	0.457	(0.307,0.567)
		λ	0.858	>1000	0.838	(0.610,1.583)
Cerrado, forest, chaco, pasture, sec.vegetation, urban, season (wet)	0.019	p	0.948	0.934	0.941	(0.877,0.968)
		ϕ	0.463	0.425	0.424	(0.264,0.580)
		λ	>1000	>1000	>1000	(>1000,>1000)
Forest, chaco, pasture, sec.vegetation, urban, agriculture, season (wet)	0.015	p	0.934	0.913	0.932	(0.810,0.954)
		ϕ	0.482	0.480	0.484	(0.349,0.598)
		λ	30.037	>1000	273.333	(0.761,>1000)
Cerrado, forest, chaco, pasture, sec.vegetation, urban, river level	0.014	p	0.932	0.910	0.929	(0.844,0.955)
		ϕ	0.487	0.470	0.468	(0.318,0.611)
Cerrado, forest, chaco, season (wet)	0.013	λ	1.088	1.244	1.189	(0.796,1.817)

		p	0.935	0.909	0.935	(0.768,0.956)
		ϕ	0.579	0.570	0.574	(0.466,0.672)
		λ	3.689	>1000	5.757	(0.808,>1000)
Cerrado, forest, chaco, pasture, agriculture, season (wet)	0.013	p	0.688	0.665	0.733	(0.228,0.934)
		ϕ	0.500	0.476	0.481	(0.295,0.643)
		λ	1.117	>1000	14.926	(0.724,>1000)
Cerrado, forest, chaco, pasture, sec.vegetation, urban, river level, season (wet)	0.012	p	0.937	0.916	0.934	(0.838,0.954)
		ϕ	0.490	0.459	0.464	(0.311,0.584)
		λ	1.123	>1000	1.260	(0.802,>1000)
Cerrado, forest, chaco, sec.vegetation, agriculture, season (wet)	0.01	p	0.942	0.926	0.938	(0.846,0.963)
		ϕ	0.556	0.541	0.547	(0.400,0.647)
		λ	0.835	>1000	1.054	(0.679,>1000)
Cerrado, forest, chaco, pasture, sec.vegetation, agriculture	0.01	p	0.932	0.921	0.929	(0.874,0.945)
		ϕ	0.468	0.491	0.495	(0.351,0.640)
		λ	1.131	1.270	1.196	(0.719,2.057)
Cerrado, chaco, pasture, season (wet)	0.009	p	0.939	0.906	0.935	(0.786,0.953)
		ϕ	0,579	0,541	0,559	(0.359,0.703)

Table 11. Population parameter estimates of the multiple abundance covariate models within 0.95 cumulative AICc weight for Great Black Hawk (*Buteogallus urubitinga*).

Models based on the binomial–zero-inflated Poisson mixture ($n = 195$ observations), where λ is the rate parameter of the Poisson distribution, p = detection probability and ϕ = zero-inflation probability.

Abundance covariates	Rescaled AICc weight	Parameter	Estimate mean	Bootstrap		
				Mean	Median	90% CI
Riverine, agriculture, sec. vegetation	0.145	λ	1.767	>1000	1.803	(1.320, 4.245)
		p	0.692	0.675	0.678	(0.501, 0.804)
		ϕ	0.462	0.450	0.452	(0.339, 0.54)
Riverine, agriculture, sec. vegetation, urban	0.082	λ	1.691	>1000	1.749	(1.182, 4.528)
		p	0.682	0.668	0.672	(0.542, 0.789)

		ϕ	0.443	0.425	0.430	(0.316, 0.535)
		λ	1.737	>1000	1.783	(1.311, 4.252)
Riverine, agriculture, sec. vegetation, season (wet)	0.081	p	0.689	0.663	0.667	(0.505, 0.807)
		ϕ	0.465	0.451	0.454	(0.340, 0.554)
		λ	2.977	>1000	3.356	(1.823, 44.919)
Riverine, sec. vegetation, urban	0.079	p	0.673	0.652	0.657	(0.499, 0.807)
		ϕ	0.514	0.502	0.502	(0.399, 0.602)
		λ	1.668	>1000	1.704	(1.263, 4.135)
Riverine, agriculture, sec. vegetation, urban, season (wet)	0.077	p	0.655	0.657	0.661	(0.520, 0.783)
		ϕ	0.449	0.437	0.438	(0.347, 0.536)
		λ	1.610	>1000	1.710	(1.096, 4.411)
Cerrado, riverine, agriculture, sec. vegetation, season (wet)	0.068	p	0.693	0.681	0.693	(0.518, 0.813)
		ϕ	0.459	0.440	0.443	(0.333, 0.549)
		λ	1.580	>1000	1.675	(1.101, 5.200)
Cerrado, riverine, agriculture, sec. vegetation, urban	0.056	p	0.696	0.675	0.678	(0.533, 0.806)
		ϕ	0.439	0.417	0.424	(0.306, 0.505)
		λ	1.390	1.483	1.398	(1.037, 1.963)
Riverine	0.056	p	0.728	0.709	0.701	(0.487, 0.933)
		ϕ	0.508	0.487	0.493	(0.357, 0.605)
		λ	2.629	>1000	3.176	(1.698, 10.688)
Riverine, sec. vegetation, urban, season (wet)	0.036	p	0.655	0.640	0.645	(0.530, 0.747)
		ϕ	0.521	0.500	0.507	(0.372, 0.600)
		λ	1.110	>1000	1.139	(0.844, 1.551)
Riverine, agriculture, urban	0.030	p	0.769	0.754	0.779	(0.535, 0.939)
		ϕ	0.433	0.426	0.429	(0.306, 0.550)
		λ	3.475	44.198	3.944	(1.456, 8.229)
Sec. vegetation	0.030	p	0.637	0.624	0.633	(0.463, 0.784)
		ϕ	0.540	0.527	0.528	(0.425, 0.616)
		λ	1.569	>1000	1.786	(1.119, >1000)
Cerrado, riverine, agriculture, sec. vegetation, urban, season (wet)	0.030	p	0.688	0.681	0.688	(0.512, 0.817)

		ϕ	0.449	0.441	0.446	(0.318, 0.546)
Agriculture, sec. vegetation, urban	0.028	λ	1.482	>1000	1.830	(1.249, >1000)
		p	0.677	0.637	0.656	(0.378, 0.786)
		ϕ	0.460	0.457	0.460	(0.342, 0.565)
Cerrado, forest, riverine, agriculture, sec. vegetation, season (wet)	0.027	λ	1.631	>1000	1.880	(1.169, 41.683)
		p	0.717	0.695	0.702	(0.535, 0.836)
		ϕ	0.476	0.458	0.465	(0.338, 0.572)
Cerrado, riverine, sec. vegetation, urban, season (wet)	0.021	λ	2.543	>1000	3.045	(1.644, 13.661)
		p	0.684	0.658	0.663	(0.506, 0.786)
		ϕ	0.518	0.502	0.502	(0.382, 0.598)
Cerrado, forest, riverine, agriculture, sec. vegetation, urban	0.017	λ	1.635	>1000	1.868	(1.198, >1000)
		p	0.704	0.691	0.694	(0.546, 0.818)
		ϕ	0.452	0.447	0.449	(0.338, 0.547)
Agriculture, sec. vegetation, urban, season (wet)	0.012	λ	1.562	>1000	1.718	(1.237, >1000)
		p	0.646	0.631	0.652	(0.417, 0.761)
		ϕ	0.466	0.453	0.455	(0.352, 0.545)
Forest, riverine, agriculture, sec. vegetation, urban, season (wet)	0.012	λ	1.610	>1000	1.734	(1.25, >1000)
		p	0.718	0.685	0.703	(0.514, 0.793)
		ϕ	0.445	0.442	0.446	(0.316, 0.545)
Cerrado, agriculture, sec. vegetation, urban, season (wet)	0.012	λ	1.355	>1000	1.499	(0.984, 3.446)
		p	0.703	0.683	0.678	(0.517, 0.845)
		ϕ	0.453	0.441	0.446	(0.338, 0.555)
Riverine, agriculture, urban, season (wet)	0.011	λ	1.165	>1000	1.261	(0.885, >1000)
		p	0.752	0.727	0.752	(0.414, 0.920)
		ϕ	0.441	0.439	0.440	(0.320, 0.561)
Cerrado, forest, riverine, agriculture, sec. vegetation, urban, season (wet)	0.010	λ	1.584	>1000	1.865	(1.143, >1000)
		p	0.699	0.691	0.699	(0.549, 0.824)
		ϕ	0.454	0.440	0.451	(0.320, 0.543)
Cerrado, chaco, riverine, agriculture, sec. vegetation, urban, season (wet)	0.010	λ	1.545	>1000	1.649	(1.104, >1000)
		p	0.692	0.685	0.688	(0.538, 0.813)

Cerrado, riverine, agriculture, urban, season (wet)	0.010	ϕ	0.445	0.428	0.437	(0.300, 0.528)
		λ	1.076	>1000	1.229	(0.826, >1000)
		p	0.774	0.744	0.779	(0.447, 0.939)
		ϕ	0.434	0.433	0.433	(0.317, 0.543)

Appendix F

Figure 1. Abundance predictions of *Cathartes* vultures (a, b), Black Vulture (c, d), Southern Crested-Caracara (e, f) and Savanna Hawk (g, h) in the Cerrado and Pantanal domains in MS state, Brazil, from the results of the multiple abundance covariate model averaging based on conditional likelihood AICc weights in low flooding - wet season (a, c, e, g) and high flooding - dry season (b, d, f, h) scenarios.

Figure 2. Abundance predictions of Aplomado Falcon (a, b), American Kestrel (c, d), White-tailed Hawk (e, f) and Roadside Hawk (g) in the Cerrado and Pantanal domains in MS state, Brazil, from the results of the multiple abundance covariate model averaging based on conditional likelihood AICc weights in low flooding - wet season (a, c, e), high flooding - dry season (b, d, f), and non-seasonal (g) scenarios.

Figure 3. Abundance predictions of Snail Kite (a, b), Black-collared Hawk (c, d) and Great black Hawk (e, f) in the Pantanal domain in MS state, Brazil, from the results of the multiple abundance covariate model averaging based on conditional likelihood AICc weights in low flooding - wet season (a, c, e), high flooding – dry season (b, d, f) scenarios.