Effects of Anthropogenic Disturbances on Habitat Use of Bornean Birds

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# Abstract

# Introduction

Land use change is driving habitat loss and biodiversity declines globally, and the highest rates of these changes are in the tropics (Newbold et al. 2015). In addition, the tropics provide most of the supply for the global trade in wildlife for pets, consumption, and medical applications (Collar and Juniper 1992, Bennett et al. 2002, Alves et al. 2010, Alves and Alves 2011, Drury 2011, Fernandes-Ferreira et al. 2012, Nóbrega Alves et al. 2013, Bush et al. 2014, McNamara et al. 2016). The effect of this demand for tropical wildlife is intensified by the increased access to intact forest provided by land use change, and in particular, the development of roads for extractive activities (i.e. logging and mining; Suárez et al. 2009, Harris et al. 2017, Symes et al. 2018).

In Indonesia, whose tropical forests are considered biodiversity hotspots (Myers et al. 2000, Brooks et al. 2002), these same processes have led to extensive deforestation from agricultural expansion, logging, and fires (Achard 2002, Sodhi et al. 2004, Hansen et al. 2013, Margono et al. 2014, Abood et al. 2015), and combined with hunting, trapping, and the illegal wildlife trade, are major drivers of species loss across the archipelago (Nijman 2010, Nijman et al. 2012, Symes et al. 2018). Furthermore, these global problems are intensified by a thriving domestic bird trade (Nijman 2010, Harris et al. 2017) encompassing thousands of species and millions of individuals (Jepson and Ladle 2005, Chng et al. 2015, 2016, 2018, Chng and Eaton 2016, Rentschlar et al. 2018). The caged bird trade and Indonesia’s rapid rate of forest decline have been implicated in avian species declines and disappearances (Collar and Juniper 1992, Collar et al. 1994, Wright et al. 2001, Jepson and Ladle 2005, Harris et al. 2017, Bergin et al. 2017).

The majority of these declines have been documented on Java, which is the most densely populated island in the world, retains a tiny proportion of its historical forest, and is the cultural and demand center of the bird trade (Burivalova et al. 2017). However, Kalimantan (Indonesian Borneo), has experienced recent and accelerating deforestation, losing an estimated 15.4% of forest between 2000-2010 alone (Miettinen et al. 2011, 2012) to massive expansion of oil palm plantations and logging enterprises combined with recent, and often associated, forest fires (Curran 2004). Concurrently, Rentschlar et al. (2018) documented the unprecedented scale of the caged bird trade in Kalimantan, but to date we are unaware of any study quantifying the effects of trade on wild birds in Kalimantan. Sumatra has experienced similar changes to Kalimantan over a similar time period, and Harris et al. (2017) found that bird market price predicted the slope of decline for Sumatran forest birds, implicating the trade in their decline. Furthermore, they found that commercially valuable birds were absent from forest less than 5 km from a road. Given this information, and expert-derived suspected declines including species found in Bornean forests (Harris et al. 2015), it is likely that commercially valuable birds in Kalimantan are disappearing even from intact and protected forests.

If these declines are occurring, and especially if they are occurring in protected areas, birds under extreme demand in the Indonesian bird trade such as Grey-cheeked Bulbul and White-rumped Shama may quickly and quietly vanish in the manner of Straw-headed Bulbul (Lee et al. 2016, Bergin et al. 2017). Author KSL was informed by a local resident of the village of Tauk that Straw-headed Bulbul was commonly spotted singing both in the forest and on the fringes of the village in the 1990s and has since vanished. Straw-headed Bulbul is an extremely charismatic bird with an incredible song and is currently the most valuable Indonesian bird in the market. While the loss of a small proportion of total species probably would not greatly affect forest ecosystem functioning, provisioning services, or regulating services, the potential for loss of cultural services and natural heritage is high. In Indonesia, the domestic bird trade developed from Javanese cultural practices of keeping birds in homes. Jepson (2010) describes how bird keepers intensively practice detailed husbandry of kept birds, enter them in song contests, teach them new song variants, and pay enormous prices for the most prized individuals. Loss of these species would preclude the continuation of this culturally significant practice. Furthermore, many forest bird species, especially colorful, large, and charismatic ones, play dominant roles in mythology, forest stewardship, and forest understanding for the Dayak and Ibon ethnic groups of Borneo (personal experience living with Dayak people). These experiences echo findings from Costa Rica, where forest birds have been found to provide more cultural services than their agriculture-associated counterparts (Echeverri et al. 2020). Lastly, ecotourism could potentially provide an alternative to extractive uses of forest and increase the well-being of local people under the right conditions (Chung et al. 2018), but the loss of charismatic and rare bird species reduces the value of forests for bird-watchers, an increasingly important group of ecotourists (Puhakka et al. 2011).

To understand how strongly trapping is affecting the distribution of commercially valuable species, we tested the hypothesis that that commercially valuable birds will be found further from roads than commercially non-valuable birds in Gunung Niyut Nature Reserve in West Kalimantan, Indonesia. We used a hierarchical community occupancy model to account for variation in detection and compared the effect of distance from roads and forest disturbance to account for edge effects.

# Methods

## Study area

Cagar Alam Gunung Niyut is an isolated preserve in the northwest corner of West Kalimantan, Indonesia. Its 124,500 hectares protect an island of intact forest surrounded by agricultural land. Of particular interest are its ~20 square kilometers of intact lowland forest in Kabupaten Landak to the southeast. Little remains of West Kalimantan’s lowland primary forest, and this section has the potential to support threatened primary forest species, and in particular, songbird species valuable in the wild bird trade. We accessed this section through the border village Tauk (Fig. 1).

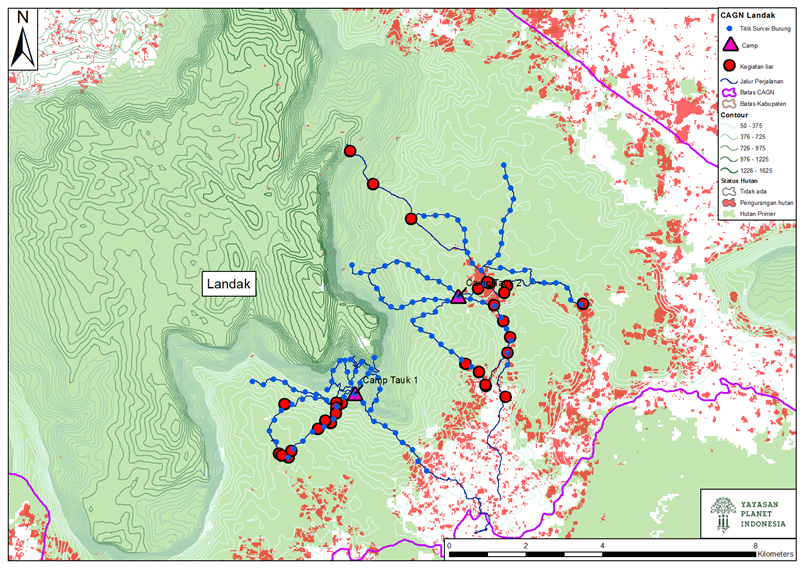


Figure 1. Study sites in Cagar Alam Gunung Niyut, Kabupaten Landak. Blue circles correspond to point count locations, pink triangles correspond to our base camps, and red circles correspond to illegal activity detected (hunting, logging, or clear-cutting for agriculture). The pink line delineates the border of Gunung Niyut Nature Preserve, red fill indicates forest loss 2011-2015, green indicates primary forest, and white indicates nonforest.

## Point counts

Two teams of three to four people, consisting of two trained observers, one local guide, and sometimes one accompanying government employee, conducted 10-minute 100 m radius point counts at points every 300 m along each of 14 transects, between 5:30 and 10am. These transects were spread in an approximately radial pattern around two base camps approximately 5 km apart, but isolated by topography. On average, each transect contained 8 points, for a total of 115 points. Almost all points were surveyed once a month from October 2017 to February 2018, for a total of five occasions per point, except for 12 points where one occasion was missed for logistical reasons. Our survey team was split into two teams that each surveyed half of the transects each month. At each point, the teams recorded the time, date, weather, and observer, then sat silently for 5 minutes before beginning to collect data. All point counts were digitally recorded. All detected individuals were recorded along with the detection method (visual or auditory) including individuals that could not be identified. For each unknown individual, time relative to the start of the point count was recorded. After data collection in the field, the primary recordist for each point count listened to the recording a second time to verify species identification and to identify calls that could not be identified in the field.

## Development of habitat covariates

In May 2018, a team of three observers recorded percent water cover at each of the 115 point count locations. In addition, we utilized remotely sensed data and GIS to characterize forest structure and condition, topography, and measures of anthropogenic disturbance hypothesized to influence avian occupancy dynamics (Table 1). Landsat 8 Surface Reflectance NDVI images were composited and cloud masked in Google Earth Engine for the study period (October 2017- February 2018) to produce mean NDVI values across the study area (Vermote et al. 2016, Gorelick et al. 2017). We calculated forest canopy disturbance metrics utilizing LandTrendr implemented in Google Earth Engine (Kennedy et al. 2018). LandTrendr is an algorithm that uses time series analysis of Landsat imagery to fit pixel-wise change trajectories of vegetation indices to identify and map forest canopy disturbance events (Lorenz et al. 2015, Cohen et al. 2018, Kennedy et al. 2018). We considered disturbance that occurred within the last ten years to be recent for primary tropical forest in Asia and so we calculated LandTrendr disturbance metrics for 2007-2017 (Canterbury et al. 2000, Cole et al. 2014). We hypothesized that species’ response to forest structure and condition may change with territory size, so these covariates were assessed at multiple spatial scales (Pearman 2002, Glisson et al. 2017). We calculated the average value of NDVI, forest height, proportion of disturbed canopy, and proportion of intact forest across buffers with radii of 100m, 500m, 1000m, and 1500m from each point count location (Glisson et al. 2017).

We calculated Euclidean distance to the nearest roads and other human disturbances including agricultural clearings, illegal logging areas, and dwellings/structures located during surveys. All spatial covariate data were processed and extracted for point count locations using ArcMap v10.6 (*ArcGIS* 2004). To determine which variables to include in our starting model set, we assessed collinearity of habitat variables using the lattice R package (Sarkar 2008). One variable out of each set of collinear variables were included in the starting model set for occupancy (Elbroch and Wittmer 2012). All covariates were scaled to 0-1 as recommended by (MacKenzie and Hines 2018).

Table 1. Habitat covariates developed for occupancy models.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Habitat  Covariate | Hypothesized  Effect | Data Product  Satellite and Sensor | Spatial Resolution | Sources |
| Normalized Difference Vegetation Index (NDVI) |  | Landsat 8 Surface Reflectance OLI/TIRS | 30m | Vermote et al. 2016, Gorelick et al. 2017 |
| Elevation, slope,  and aspect |  | ASTER Global Digital Elevation Model V002 | 30m | NASA LP DAAC 2011 |
| Forest canopy height  ( canopy cover > 5m) |  | Forest Canopy Height Map; derived from Geoscience Laser Altimeter System (GLAS) LiDAR | 1000m | Simard et al. 2011 |
| Proportion of canopy recently disturbed (2007-2017) | Species specific response to disturbance levels | LandTrendr disturbance metrics: Landsat 7 TM & Landsat 8 OLI/TIRS TOA b | 30m | Kennedy et al. 2010; Kennedy et al. 2018 |
| Proportion of intact forest in 2016 |  | REG Borneo Forest Cover 2016; derived from Landsat 5,7, & 8 | 30m | Gaveau 2017 |
| Distance to roads |  | Open Street Map Kalimantan roads layer | 30m | OpenStreetMap contributors (2015) |

## Occupancy model

We used a multispecies single-season occupancy model to estimate the effects of habitat covariates, disturbed canopy, distance from roads, and commercial demand on the occupancy probability of 115 sites for a community of 206 bird species, while also accounting for imperfect detection (Kery and Schaub 2011). We assumed that the true state of occupancy (*zi,j*) for species *i* and site *j* resulted from the probability of occupancy (*ψi,j*) for species *i* and site *j* such that

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We assumed that the state of detection or non-detection (*yi,j,k*) for each species *i* at each point count location *j* and occasion *k* given the true state of occupancy (*zi,j*) for each species *i* at each point *j* resulted from true occupancy (*zi,j*) of species *i* and point *j* and detection probability (*pi,j,k*) of species *i* at point *j* and occasion *k* such that

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We modeled detection (*pi,j,k*) as

We modeled occupancy probability (*ψi,j*) as

Parameters in the *α* family were simple fixed effect terms. Parameters in the *β* family were estimated for each species, with species terms drawn from a normal distribution of mean and variance estimated from the data. Parameters in the *δ* and *γ* families were random intercepts (variance estimated from the data around a mean of 0) designed to incorporate additional variation for each species or site that could not be explained by other fixed or random effects.

All habitat and point count covariates were standardized and scaled to a 0-1 range as recommended by Kery and Schaub (2011). While we detected 206 species in total, we excluded those species with fewer than 10 detections to reduce the number of uninformative posterior parameters. In addition, we excluded *Rhinoplax vigil* because its mobile lifestyle and far-reaching call ensure that our point counts were not far enough apart for spatial independence, which violates one of the key assumptions of occupancy modeling. To account for spatial autocorrelation, we grouped points by transect. We fitted the model to our point count data using Markov Chain Monte Carlo simulation to calculate the posterior distribution for each parameter. Our models were implemented in JAGS (Plummer 2017) and run using the R package R2jags (Su and Yajima 2020). Non-informative priors were used throughout. Specifically, means and fixed effects were drawn from a normal(0, 100) distribution and sigma terms were drawn from a uniform(0, 10) distribution. We iterated over the model 50,000 times with a thinning interval of 20 and 20,000 iterations of burn-in, resulting in 1,500 samples of the posterior. We checked convergence by visually inspecting trace plots and with the Gelman-Rubin convergence diagnostic (Gelman and Rubin 1992), ensuring that all values were less than 1.1. For full code, see supplemental information.

We extracted the posterior distribution for all parameter estimates detailing how each species responded to each microhabitat variable and interactions with commercial value (i.e., *β*1-6). Microhabitat variables and interactions were considered to significantly affect species on average when the 95% Bayesian credible interval (BCI) for the mean (l) of the random effect distribution governing species’ responses did not overlap 0. We considered there to be significant variability among species in their responses when the corresponding *σ* of the distribution was greater than 0.

arameters in the a and g families were simple fixed

effect terms. All parameters in the b and h families were

estimated for each species, with species terms drawn

from a normal distribution of mean (l) and variance

(r

2

) estimated from the data. c and d terms were random

intercepts (variance estimated from data around a mean

of 0) designed to incorporate additional variation for

each species, site, or replicate that could not be explained

by other fixed and random effects

# Results

We detected a total of 206 species. 95 species were detected at least ten times and 111 were detected less than ten times. The five most frequently detected species were *Psilopogon australis, Psilopogon chrysopogon, Psilopogon mystacophanos, Arachnothera longirostra, Pycnonotus erythropthalmos,* and *Alcippe brunneicauda*. We detected seven species that are either sold at high prices as pets (Lee et al. 2016, Rentschlar et al. 2018) or sale of its casque (Helmeted Hornbill: *Rhinoplax vigil*): *Alophoixus tephrogenys* (10 detections), *Chloropsis sonnerati* (11 detections), *Copsychus malabaricus* (39 detections), *Hydrornis schwaneri* (1 detection), *Irena puella* (64 detections), *Loriculus galgulus* (83 detections), *Platylophus galericulatus* (2 detections),  *R. vigil* (74 detections), and *Spilornis cheela* (20 detections). However, because *P*. *galericulatus* and *H. schwaneri* were only detected 2 and 1 times respectively, we did not have enough data on these species to produce informative posterior distributions using occupancy modeling.

## Detection probability

Detection varied between observers. Birds were more likely to be detected earlier in the day, and detection varied significantly among both sites and species, though much more among species (*σ* = 0.16 and 4.55, respectively; see Table 2).

Table 2. Simulated parameter values

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | "mean" | "2.5%" | "97.5%" | "Rhat" | "n.eff" | "SD" |
| "p.obs" | 0.924364417145114 | 0.779652329182907 | 1.05541934329341 | 1.00115420617856 | 1400 | NA |
| "p.time" | -0.716056264686161 | -0.903663624735106 | -0.534307672873224 | 1.00019847608512 | 1400 | NA |
| "sigma.p.site" | 0.172058161310346 | 0.112583316939874 | 0.233648942466958 | 1.0094277089288 | 430 | NA |
| "sigma.p.sp" | 3.02917588158505 | 2.62190967738406 | 3.51255805656856 | 1.00020065700363 | 1400 | NA |
| "mu.lambda.ch" | 0.0887688247007165 | -0.894487308241117 | 1.07110356641374 | 1.00277981098968 | 780 | 0.716088265300204 |
| "mu.lambda.dr" | 2.61048660769247 | 0.932586964635411 | 4.58909739582093 | 1.00954121541369 | 380 | 3.03065598025529 |
| "mu.lambda.dr.com" | 4.67559279332337 | -0.877440262536719 | 11.9318682214019 | 1.04962358929461 | 61 | 3.21432627848932 |
| "mu.lambda.intf" | 1.70476903873963 | 0.691789993380472 | 2.87500507652365 | 1.00104755839494 | 1400 | 1.40733348596534 |
| "mu.lambda.intf.com" | 0.197715385043125 | -3.377298576588 | 6.52225818475202 | 1.04274289758644 | 80 | 3.27657667273277 |
| "mu.lambda.water" | -0.604997556361512 | -1.55429517424755 | 0.473865929278189 | 1.00652590508824 | 360 | 1.26889389028441 |
| "sigma.lambda.site" | 0.222789198711023 | 0.009115861465455 | 0.527990901201549 | 1.02507519040454 | 210 | NA |
| "sigma.lambda.transect" | 0.448417034627037 | 0.0615653582653295 | 0.934435207630699 | 1.00547045431351 | 900 | NA |

## Are commercially valuable species more likely to occupy sites further from roads than commercially non-valuable species?

Species were significantly more likely to occupy sites that were further from roads. Commercially valuable species were more likely to live further from roads than commercially non-valuable species. The posterior distribution of the multiplicative effect of commercial value (i.e. valuable or not) and distance from roads did not meet 95% significance, but meets 90% significance, and the mean is strongly positive (2.5%: -0.88, mean: 4.68, 97.5%: 11.93; see Fig. 2 and Table 2). Occupancy for commercially valuable species increased with a higher slope over the distance to roads gradient than for commercially non-valuable species (Fig. 2).

A close up of a logo

Description automatically generated

Figure 2. Commercially valuable species tend to be found very close or very far from roads. Dots indicate the simulated mean, and lines indicate the 95% confidence interval. Blue lines indicate commercially valuable species, and red lines indicate commercially non-valuable species.

## Are commercially valuable species more likely to occupy sites with higher percentages of intact forest than commercially non-valuable species?

While all species were significantly more likely to occupy sites with higher percent intact forest, commercially valuable species were not more likely to occupy sites with higher percentages of intact forest than commercially non-valuable species (Table 2).

# Discussion

Our results highlight the sensitivity of primary rainforest species to habitat disturbance, with the average species likely to occupy sites further from roads and with more intact forest. Encouragingly, our results do not suggest that commercially valuable birds in this protected area are subject to the intertwined one-two punch of heightened sensitivity to habitat loss and wildlife trade. The average commercially valuable species may occupy sites further from roads than commercially non-valuable species. The trend that we documented, while not highly significant, probably suffered from low power because few species were considered commercially valuable and most of those species were detected infrequently. This trend suggests either extreme trapping pressure or an avoidance effect. Because we did not measure density, we cannot directly distinguish between these two effects.

While it is possible that only trapped species would learn to avoid humans, Bötsch et al. (2018) suggest that the presence of humans increases perceived predation risk for most birds. Furthermore, several of the commercially valuable species (e.g. *C. sonnerati*, *C. malabaricus*, *A. tephrogenys*, *I. puella*, *P. galericulatus*) were classified as threatened by trade based on severe declines that have already occurred on Java and Sumatera (Lee et al. 2016), so we caution against dismissing these possible declines out of hand. If these declines are indeed occurring, the pull of demand for songbirds reaches very far indeed from urban Java into very remote, rural areas of the archipelago. As access to rural forests continues to increase, and globalization weakens indigenous control over forests and resources, the last refuges for these species will quickly vanish.

*Biases and possible weaknesses of this study*

Team 1 frequently observed some species that were not expected to be common and were very rarely observed by Team 2 (e.g. *Arachnothera flavigaster* observed 26 times by Team 1 and 1 time by Team 2, and expected to be “uncommon” based on Birds of the Indonesian Archipelago). In addition, Team 2 observed many common species many more times than Team 1 (e.g. *Loriculus galgulus* observed 0 times by Team 1 and 83 times by Team 2, and expected to be “fairly common” based on Birds of the Indonesian Archipelago). Team 2 was led by a team member with 2+ years of experience identifying Bornean bird calls, and Team 1 had only been provided a month-long training before the start of the project, so this bias is expected to relate to misidentification and detection that is biased towards loud and complex song types. Indeed, species underreported by Team 1 tended to have quieter, simpler, and/or higher-pitched calls, or were extremely common (e.g. all of the *Prionochilus*, *Loriculus galgulus*, *Dicaeum trigonostigma*, *Cyanoderma rufifrons*, *Arachnothera longirostra*, *Aegithina viridissima*).

## Recommendations

As recommended by Rentschlar (2018), strategies to mitigate illegal poaching of songbirds must be multi-pronged and engage all stakeholders. Most critically, these songbirds must be nationally protected. Regrettably, after the Conservation Act No. 5 of 1990 was updated in 2018, the songbird keeper community pressured the removal of some of the most valuable and overexploited species (Straw-headed Bulbul, which is classified by the IUCN as Critically Endangered). This unfortunate about-face puts these birds at risk once again and highlights the massive domestic demand for them. Furthermore, it highlights the disconnect between urban bird keepers and the source of their pets. We echo calls by many others (Chng and Eaton 2016, Chng *et al*. 2015, Jepson and Ladle 2005) for Indonesia to finally protect the species of concern recommended by the Asian Songbird Crisis Summit (Lee *et al*. 2015).

Until education and behavior change campaigns are able to address the root causes, prices for rare birds will continue to rise and tempt poachers into protected areas. We also echo Rentschlar *et al*. (2018) in their assertion that captive breeding cannot mitigate demand for wild birds in Kalimantan in the absence of comprehensive regulation and enforcement.

Our results highlight the obvious: most species depend on primary forest for their survival, and therefore, any ongoing deforestation of Cagar Alam Gunung Niyut (CAGN) must halt immediately. Though Gaveau (2017) estimates that 50% of the island remains forested, CAGN is an island of forest in an area that was deforested mainly in the 1980s and 1990s (Global Forest Watch 2018), and remains one of West Kalimantan’s last large plots of intact forest. This remnant habitat must be protected. To reach this objective, conservationists and policymakers must work with communities living in and near CAGN to understand the proximate causes of deforestation and help alleviate the poverty that may drive local people to log and trap.

This study documents the effects of illegal trapping activity on wild populations of threatened songbirds. Despite residing within a Nature Preserve (*Cagar Alam*) whose official rules prohibit harvesting of any kind, valuable songbird populations are showing signs of trapping pressure in this isolated park. Furthermore, we detected no individuals of Straw-headed Bulbul during this study, which indicates that past trapping pressure reached deep into the park. If indeed Straw-headed Bulbul was trapped out of the Preserve in the past, currently valuable species could be trapped out in the future. However, the presence of threatened songbirds documented here underscores how vital it is to protect Cagar Alam Gunung Niyut.

# References

Abood, S. A., J. S. H. Lee, Z. Burivalova, J. Garcia-Ulloa, and L. P. Koh. 2015. Relative Contributions of the Logging, Fiber, Oil Palm, and Mining Industries to Forest Loss in Indonesia: Deforestation among Indonesia’s industries. Conservation Letters 8:58–67.

Achard, F. 2002. Determination of Deforestation Rates of the World’s Humid Tropical Forests. Science 297:999–1002.

Alves, R. R., and H. N. Alves. 2011. The faunal drugstore: Animal-based remedies used in traditional medicines in Latin America. Journal of Ethnobiology and Ethnomedicine 7:9.

Alves, R. R. N., W. M. S. Souto, and R. R. D. Barboza. 2010. Primates in traditional folk medicine: a world overview. Mammal Review 40:155–180.

ArcGIS. 2004. . Environmental Systems Research Institute (ESRI), Redlands, CA, USA.

Bennett, E. L., E. J. Milner-Gulland, M. Bakarr, H. E. Eves, J. G. Robinson, and D. S. Wilkie. 2002. Hunting the world’s wildlife to extinction. Oryx 36.

Bergin, D., S. C. Chng, J. A. Eaton, and C. R. Shepherd. 2017. The final straw? An overview of Straw-headed Bulbul Pycnonotus zeylanicus trade in Indonesia. Bird Conservation International:1–7.

Bötsch, Y., Z. Tablado, D. Scherl, M. Kéry, R. F. Graf, and L. Jenni. 2018. Effect of Recreational Trails on Forest Birds: Human Presence Matters. Frontiers in Ecology and Evolution 6:175.

Brooks, T. M., R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, A. B. Rylands, W. R. Konstant, P. Flick, J. Pilgrim, S. Oldfield, G. Magin, and C. Hilton-Taylor. 2002. Habitat Loss and Extinction in the Hotspots of Biodiversity. Conservation Biology 16:909–923.

Burivalova, Z., T. M. Lee, F. Hua, J. S. H. Lee, D. M. Prawiradilaga, and D. S. Wilcove. 2017. Understanding consumer preferences and demography in order to reduce the domestic trade in wild-caught birds. Biological Conservation 209:423–431.

Bush, E. R., S. E. Baker, and D. W. Macdonald. 2014. Global Trade in Exotic Pets 2006-2012. Conservation Biology 28:663–676.

Canterbury, G. E., T. E. Martin, D. R. Petit, L. J. Petit, and D. F. Bradford. 2000. Bird Communities and Habitat as Ecological Indicators of Forest Condition in Regional Monitoring. Conservation Biology 14:544–558.

Chng, S. C., and J. A. Eaton. 2016. In the market for extinction: Eastern and Central Java. TRAFFIC, Petaling Jaya, Selangor, Malaysia.

Chng, S. C. L., J. A. Eaton, K. Krishnasamy, C. R. Shepherd, and V. Nijman. 2015. In the market for extinction: An inventory of Jakarta’s bird markets. TRAFFIC Southeast Asia, Petaling Jaya, Selangor, Malaysia.

Chng, S. C. L., M. Guciano, and J. A. Eaton. 2016. In the market for extinction: Sukahaji, Bandung, Java, Indonesia:8.

Chng, S. C. L., C. R. Shepherd, and J. A. Eaton. 2018. In the market for extinction: birds for sale at selected outlets in Sumatra. TRAFFIC Bulletin 30:8.

Chung, M. G., T. Dietz, and J. Liu. 2018. Global relationships between biodiversity and nature-based tourism in protected areas. Ecosystem Services 34:11–23.

Cohen, W. B., Z. Yang, S. P. Healey, R. E. Kennedy, and N. Gorelick. 2018. A LandTrendr multispectral ensemble for forest disturbance detection. Remote Sensing of Environment 205:131–140.

Cole, L. E. S., S. A. Bhagwat, and K. J. Willis. 2014. Recovery and resilience of tropical forests after disturbance. Nature Communications 5:3906.

Collar, N. J., M. Crosby, and A. Statterfield. 1994. Birds to Watch 2: The World List of Threatened Birds. BirdLife International, Cambridge, UK.

Collar, N. J., and A. Juniper. 1992. Dimensions and causes of the parrot conservation crisis. Pages 1–24 *in* S. R. Beissinger and N. Snyder, editors. New World parrots in crisis: solutions from conservation biology. Smithsonian Institute Press, Washington, DC, USA.

Curran, L. M. 2004. Lowland Forest Loss in Protected Areas of Indonesian Borneo. Science 303:1000–1003.

Drury, R. 2011. Hungry for success: Urban consumer demand for wild animal products in Vietnam. Conservation and Society 9:247.

Echeverri, A., D. S. Karp, R. Naidoo, J. A. Tobias, J. Zhao, and K. M. A. Chan. 2020. Can avian functional traits predict cultural ecosystem services? People and Nature 2:138–151.

Elbroch, L. M., and H. U. Wittmer. 2012. Puma spatial ecology in open habitats with aggregate prey. Mammalian Biology 77:377–384.

Fernandes-Ferreira, H., S. V. Mendonça, C. Albano, F. S. Ferreira, and R. R. N. Alves. 2012. Hunting, use and conservation of birds in Northeast Brazil. Biodiversity and Conservation 21:221–244.

Gaveau, D. L. A. 2017. What a difference 4 decades make : Deforestation in Borneo since 1973. CIFOR:1–4.

Gelman, A., and D. B. Rubin. 1992. Inference from Iterative Simulation Using Multiple Sequences. Statistical Science 7:457–472.

Glisson, W. J., C. J. Conway, C. P. Nadeau, and K. L. Borgmann. 2017. Habitat models to predict wetland bird occupancy influenced by scale, anthropogenic disturbance, and imperfect detection. Ecosphere 8:e01837.

Global Forest Watch. 2018. Tree Cover Loss in Kalimantan Barat. https://www.globalforestwatch.org/dashboards/country/IDN/12/9.

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore. 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment 202:18–27.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 342:850–853.

Harris, J. B. C., J. M. H. Green, D. M. Prawiradilaga, X. Giam, Giyanto, D. Hikmatullah, C. A. Putra, and D. S. Wilcove. 2015. Using market data and expert opinion to identify overexploited species in the wild bird trade. Biological Conservation 187:51–60.

Harris, J. B. C., M. W. Tingley, F. Hua, D. L. Yong, J. M. Adeney, T. M. Lee, W. Marthy, D. M. Prawiradilaga, C. H. Sekercioglu, Suyadi, N. Winarni, and D. S. Wilcove. 2017. Measuring the impact of the pet trade on Indonesian birds: Bird Declines from Pet Trade. Conservation Biology 31:394–405.

Jepson, P. 2010. Towards an Indonesian bird conservation ethos: Reflections from a study of bird-keeping in the cities of Java and Bali. Pages 331–330 Ethno-ornithology: Birds, indigenous peoples, culture and society. Earthscan.

Jepson, P., and R. J. Ladle. 2005. Bird-keeping in Indonesia: conservation impacts and the potential for substitution-based conservation responses. Oryx 39:442.

Kennedy, R., Z. Yang, N. Gorelick, J. Braaten, L. Cavalcante, W. Cohen, and S. Healey. 2018. Implementation of the LandTrendr Algorithm on Google Earth Engine. Remote Sensing 10:691.

Kery, M., and M. Schaub. 2011. Bayesian Population Analysis using WinBUGS: A Hierarchical Perspective. Elsevier Science.

Lee, J. G. H., S. C. L. Chng, and J. A. Eaton. 2016. Conservation strategy for Southeast Asian songbirds in trade. Wildlife Reserves Singapore/TRAFFIC, Singapore.

Lorenz, T. J., K. T. Vierling, J. M. Kozma, J. E. Millard, and M. G. Raphael. 2015. Space use by white-headed woodpeckers and selection for recent forest disturbances: White-Headed Woodpecker Space Use. The Journal of Wildlife Management 79:1286–1297.

MacKenzie, D. I., and J. Hines. 2018. RPresence: R Interface for Program PRESENCE.

Margono, B. A., P. V. Potapov, S. Turubanova, F. Stolle, and M. C. Hansen. 2014. Primary forest cover loss in Indonesia over 2000–2012. Nature Climate Change 4:730–735.

McNamara, J., M. Rowcliffe, G. Cowlishaw, J. S. Alexander, Y. Ntiamoa-Baidu, A. Brenya, and E. J. Milner-Gulland. 2016. Characterising Wildlife Trade Market Supply-Demand Dynamics. PLOS ONE 11:e0162972.

Miettinen, J., C. Shi, and S. C. Liew. 2011. Deforestation rates in insular Southeast Asia between 2000 and 2010. Global Change Biology 17:2261–2270.

Miettinen, J., C. Shi, W. J. Tan, and S. C. Liew. 2012. 2010 land cover map of insular Southeast Asia in 250-m spatial resolution. Remote Sensing Letters 3:11–20.

Myers, N., R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent. 2000. Biodiversity hotspots for conservation priorities. Nature 403:853–858.

NASA LP DAAC. 2011. ASTER Global Digital Elevation Model. Version 2. NASA EOSDIS Land Processes DAAC, USGS Earth Resources and Science (EROS) Center, Souix Falls, SD, USA.

Newbold, T., L. N. Hudson, S. L. L. Hill, S. Contu, I. Lysenko, R. A. Senior, L. Börger, D. J. Bennett, A. Choimes, B. Collen, J. Day, A. De Palma, S. Díaz, S. Echeverria-Londoño, M. J. Edgar, A. Feldman, M. Garon, M. L. K. Harrison, T. Alhusseini, D. J. Ingram, Y. Itescu, J. Kattge, V. Kemp, L. Kirkpatrick, M. Kleyer, D. L. P. Correia, C. D. Martin, S. Meiri, M. Novosolov, Y. Pan, H. R. P. Phillips, D. W. Purves, A. Robinson, J. Simpson, S. L. Tuck, E. Weiher, H. J. White, R. M. Ewers, G. M. MacE, J. P. W. Scharlemann, and A. Purvis. 2015. Global effects of land use on local terrestrial biodiversity. Nature 520:45–50.

Nijman, V. 2010. An overview of international wildlife trade from Southeast Asia. Biodiversity and Conservation 19:1101–1114.

Nijman, V., C. R. Shepherd, Mumpuni, and K. L. Sanders. 2012. Over-exploitation and illegal trade of reptiles in Indonesia. Herpetological Journal 22:83–89.

Nóbrega Alves, R. R., J. R. De Farias Lima, and H. F. P. Araujo. 2013. The live bird trade in Brazil and its conservation implications: an overview. Bird Conservation International 23:53–65.

Pearman, P. B. 2002. THE SCALE OF COMMUNITY STRUCTURE: HABITAT VARIATION AND AVIAN GUILDS IN TROPICAL FOREST UNDERSTORY. Ecological Monographs 72:19–39.

Plummer, M. 2017. JAGS - Just Another Gibbs Sampler.

Puhakka, L., M. Salo, and I. E. Sääksjärvi. 2011. Bird Diversity, Birdwatching Tourism and Conservation in Peru: A Geographic Analysis. PLoS ONE 6:e26786.

Rentschlar, K. A., A. E. Miller, K. S. Lauck, M. Rodiansyah, Bobby, Muflihati, and Kartikawati. 2018. A Silent Morning: The Songbird Trade in Kalimantan, Indonesia. Tropical Conservation Science 11:194008291775390.

Sarkar, D. 2008. Lattice: Multivariate Data Visualization with R. Springer, New York.

Simard, M., N. Pinto, J. B. Fisher, and A. Baccini. 2011. Mapping forest canopy height globally with spaceborne lidar. Journal of Geophysical Research 116:G04021.

Sodhi, N. S., L. P. Koh, B. W. Brook, and P. K. L. Ng. 2004. Southeast Asian biodiversity: an impending disaster. Trends in Ecology & Evolution 19:654–660.

Su, Y.-S., and M. Yajima. 2020. Package 'R2jags’: Using R to Run “JAGS”.

Suárez, E., M. Morales, R. Cueva, V. Utreras Bucheli, G. Zapata-Ríos, E. Toral, J. Torres, W. Prado, and J. Vargas Olalla. 2009. Oil industry, wild meat trade and roads: indirect effects of oil extraction activities in a protected area in north-eastern Ecuador. Animal Conservation 12:364–373.

Symes, W. S., D. P. Edwards, J. Miettinen, F. E. Rheindt, and L. R. Carrasco. 2018. Combined impacts of deforestation and wildlife trade on tropical biodiversity are severely underestimated. Nature Communications 9:4052.

Vermote, E., C. Justice, M. Claverie, and B. Franch. 2016. Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Remote Sensing of Environment 185:46–56.

Wright, T. F., C. A. Toft, E. Enkerlin-Hoeflich, J. Gonzalez-Elizondo, M. Albornoz, A. Rodríguez-Ferraro, F. Rojas-Suárez, V. Sanz, A. Trujillo, S. R. Beissinger, V. Berovides A, G. A. Xiomara, A. T. Brice, K. Joyner, J. Eberhard, J. Gilardi, S. Koenig, S. Stoleson, P. Martuscelli, J. M. Meyers, K. Renton, A. M. Rodríguez, A. C. Sosa-Asanza, F. J. Vilella, and J. W. Wiley. 2001. Nest poaching in Neotropical parrots. Conservation Biology 15:710–720.