Using Occupancy Models to Assess Illegal Wildlife Trade Patterns across the Philippines

Julius Bronola

ABSTRACT

This study investigates the spatiotemporal patterns of illegal wildlife trade (IWT) in the Philippines from 2010 to 2019 and identifies influential physical and socioeconomic factors. The Philippines, a biodiversity hotspot with high levels of insular endemism and species-rich rainforests, faces a biodiversity crisis due to overexploitation of wildlife species. A multi-season occupancy model was employed to test hypotheses that examine the influence of accessibility, target richness, effort required to distribute illicit goods, and the quality of life of IWT participants on the occupancy, initiation, persistence, and detection of IWT activity. The top-ranking model indicated that the probability of IWT initiation decreases with increasing distance from a KBA to the nearest airport and increases with the log of human population density. Further, detection of IWT activity within a province increases with road density and the proportion of key biodiversity areas. These findings can guide the Philippine's anti-IWT strategies, pinpointing which provinces need targeted policies, initiatives, and public education programs to prevent, better detect, and understand IWT activity.

KEYWORDS

Environmental criminology, GIS, human population density, illegal wildlife trade, key biodiversity areas, occupancy models, Philippines, road density, spatial analysis

INTRODUCTION

The tropics contain some of the world's most diverse terrestrial and marine ecosystems. However, this biome is also under significant biological threat due to various factors such as habitat loss, natural resource overexploitation, pollution, climate change, and the introduction of invasive species (Hughes 2017). One of the primary drivers contributing to the tropical biodiversity crisis is the overexploitation of wildlife species through poaching and involvement in illegal wildlife trade (IWT). These activities have aggravated the rapid decline of species over the past 20-30 years and have resulted in severe ecological consequences (Harrison et al. 2016). In a recent meta-analysis of 176 studies focusing on hunting in the tropics, Benitez-Lopez et al. (2017) demonstrated that overall tropical bird populations declined by 58% and mammal populations declined by 83% due to overexploitation. Since many poached and illegally traded species play essential roles in forest ecosystems, such as seed dispersal and predation, their rapid decline could accelerate detrimental cascading effects on understory and overstory dynamics, succession, and overall composition (Corlett 2007). Moreover, the global movement of wildlife and their increased interaction with humans through IWT networks have influenced the emergence and spread of zoonotic diseases and ecological invasions (Rosen and Smith 2010). Addressing these grave consequences necessitates an integrated approach that evaluates the interconnected ecological and socioeconomic dimensions of illegal wildlife trade networks.

Detecting, monitoring, and predicting incidents of illegal wildlife trade (IWT) can pose inherent difficulties due to various social, economic, and political factors that drive such activities. For instance, some individuals rely on wildlife for basic sustenance or recreational purposes, while others engage in hunting to safeguard their property, prevent conflicts, or preserve cultural traditions (Corlett 2007). Nonetheless, the majority of contemporary IWT activities are motivated by commercial incentives, leading to a significant increase in demand for traditional medicine, luxury goods, and exotic pets, creating a market valued at approximately $20 billion annually (Hughes 2017). Additionally, the rapid expansion of human settlements and commercial developments has resulted in the encroachment into natural habitats, facilitating easier access for illegal wildlife harvesting (Benitez-Lopez et al. 2017). To examine the intricate relationships between hunting pressures and biodiversity, researchers have utilized occupancy modeling as a robust inferential framework. This technique employs species occurrence data to estimate the probabilities of species presence and detection within specific locations, while considering potential imperfections in detection methods. Essentially, occupancy models offer a quantitative approach for predicting patterns of species distribution (MacKenzie et al. 2018). In the context of IWT activity, researchers can develop models capable of forecasting the spatiotemporal distribution of illegal hunting events, confiscations, or seizures across a landscape by considering specific ecological and socio-economic variables. These variables may include distances to nearest roads and settlements, the extent of ranger patrolling efforts, or the demographic characteristics of a region (Moore et al. 2018).

Within the tropical region of Southeast Asia, the Philippines holds a considerable portion of the planet's biodiversity, due to its high levels of insular endemism and species-rich rainforests (Scheffers et al. 2012). However, because of the country's high levels of poverty and lack of alternative livelihoods, many people overexploit the archipelago's wild fauna as a means of survival, relying on wildlife as an inexpensive food source or trafficking highly prized species as a source of income (Scheffers et al. 2012, BMB-DENR 2016). However, it is difficult to track the exact impacts of wildlife hunting and trade, and are often overlooked in the Philippines, resulting in almost no studies of the country's hunting practices and their influence on both targeted and non-targeted species (Scheffers et al. 2012).

This thesis aims to analyze the spatiotemporal patterns of illegal wildlife trade activity across the 81 provinces of the Philippines from 2010 to 2019, and identify the physical and socioeconomic variables that have influenced it. Considering that accessibility, target richness, least cost effort, and quality of life are among the factors associated with IWT activity, I addressed the following three questions: 1) How have road density and the proportion of key biodiversity areas (KBAs) affected the occupancy dynamics of IWT activity across the Philippines?, 2) How have the proximities between KBAs, transportation ports (e.g., airports and seaports) and market centers affected the occupancy dynamics of IWT activity across the Philippines?, and 3) Have human population density, poverty levels, and crime rates affected the occupancy dynamics of IWT activity across the Philippines? I generated a set of dynamic occupancy models that utilized a mixture of IWT incidence data (i.e., confiscations and seizures) and publicly available geospatial and demographic datasets to test the following hypotheses: a) road densities and proportion of KBAs will have a positive correlation with IWT occurrence, detection, and persistence, b) distances to key biodiversity areas, transportation ports, and market centers will show a negative correlation with IWT occurrence and persistence, and c) crime rates, population densities, and poverty levels will have a positive correlation with IWT occurrence, detection and persistence.

Study area

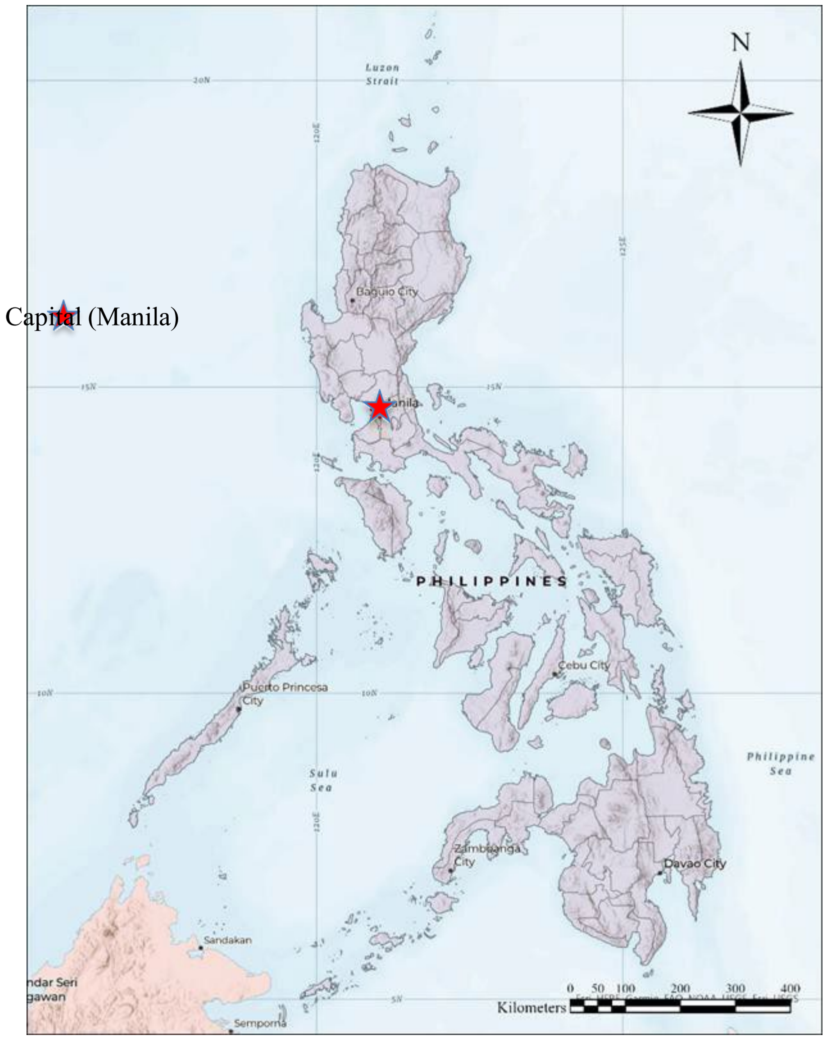

Figure 1. Study area is the Philippines, a Southeast Asian country comprised of > 7,000 tropical islands (13°00'N, 122°00'E). Lines represent the administrative boundaries delineating each province.

The study area for this thesis is the Philippines, a Southeast Asian country situated entirely within the tropical zone (Figure 1). The country is located approximately 800 km away from the Asian mainland, between Taiwan and Borneo, bordered on the east by the vast expanse of the

Pacific Ocean, and on the west by the South China Sea, separating it from Vietnam and China. The physical shape of the Philippines is elongated and fragmented, composed of 7,107 islands, with a total land area of 299,000 square kilometers. The country is characterized by its mountainous terrain, with steep slopes and few roads (Beerepoot 2018). The country has a wide range of habitats, including mossy forests, wetlands, lush tropical forests, and marine and coastal ecosystems, with a coastline of over 36,000 km. The Philippines is considered one of the world's 36 biodiversity hotspots. It is home to over 9,000 native vascular plant species, more than 1,500 species of terrestrial and marine vertebrates combined, and over 500 species of coral. A significant percentage of these species, ranging from 34% to 88%, are endemic to the country (Fischer 2021). The Philippines is divided into 17 regions, which group 81 provinces based on geographical, linguistic, historical, and ethnic characteristics. These provinces are the primary political and administrative divisions, each with its own legislative body and elected governor. These provinces are further subdivided into municipalities and cities (Beerepoot 2018).

Occupancy models

Key theory and concepts

The principal purpose of an occupancy model is to accurately estimate species occurrences and occupancy dynamics at specific study sites while accounting for imperfect detections during surveys (MacKenzie et al. 2018). A typical occupancy study design, as described by Bailey et al. (2013), involves the following specific fundamental components and must adhere to certain assumptions.

The primary parameter generated by these models is occupancy (ψ), defined as the probability of a species occupying a randomly selected site within the study area. Although a single survey across a representative sample of sites can essentially estimate the proportion of area occupied by the target species, it is not guaranteed that a species will be detected during this survey even when present at a site, resulting in a biased estimation of true occupancy. To resolve this issue, we can perform repeated surveys at each site within a specific timeframe (referred to as a "season"), generating a separate estimate (p) that describes the probability of detecting the species at an occupied site during an independent survey. Thus, integrating p into ψ as a conditional parameter provides a more unbiased estimate of the species' true occupancy (Bailey et al. 2013; MacKenzie et al. 2018).

The conditions outlined above represent occupancy as a static process, which is rarely the case considering the tendency of organisms to move across space and time. Incorporating multiple seasons of repeated surveys introduces a temporal dimension to the modeling framework, generating two vital rate parameters: colonization (γ) and local extinction (ε). The colonization parameter (γ) describes the probability of an unoccupied site becoming occupied across successive seasons, whereas the local extinction parameter (ε) describes the reverse process (Bailey et al. 2013; MacKenzie et al. 2018).

Another utility of occupancy models involves the a priori selection of covariates that operate as possible determinants of each parameter. These covariates can be continuous or categorical variables representing an array of biotic, abiotic, spatiotemporal, methodological, or socioeconomic factors influencing the occupancy dynamics of a species. Including covariates introduces a model comparison step into the analysis, whereby each probabilistic parameter can be defined as a deterministic function of various covariate combinations, generating models that each represent an alternative hypothesis. By identifying the model that best fits the observed data, we can draw inferences about which factors have a significant impact on the occupancy dynamics of the target species and eventually use that model to build retrospective and predictive tools (MacKenzie et al. 2018).

Applying the framework to my study system

To estimate the trends in IWT incidents across the 81 provinces of the Philippines from 2010 to 2019, I used the multi-season occupancy framework introduced by MacKenzie et al. (2018). Given my study system, I considered one or more reports of IWT incidents from a province within an annual quarter as detection of on-going poaching activity during that respective year. In case an IWT incident was not detected in a province during an annual quarter within the year, it could have either meant that there was no IWT activity taking place in the province during the year or that IWT activity was taking place, but went undetected. The following equation represents the likelihood of these detection and nondetection scenarios:

$$L(\psi, p) = [\overbrace{\psi^n \prod_{j=1}^{K} p_j^{n_j}(1-p_j)^{n-n_j}}^{\text{detection}}] \times [\overbrace{\psi \prod_{j=1}^{Q}(1-p_j) + (1-\psi)}^{\text{nondetection}}]^{N-n} \tag{1}$$

where

$L(\psi, p) =$	combined model likelihood
$\psi =$	probability that IWT activity is occurring in a province during a year
$p_j =$	probability that IWT activity will be detected during an annual quarter j, given its occurrence
$N =$	total number of provinces from where data was collected
$K =$	number of quarters in a year
$n_j =$	number of provinces where IWT activity was detected in annual quarter j
$n =$	Total number of provinces where IWT activity was detected at least once during the year

To include the probabilities of initiation (γ) and discontinuation (ε) of IWT incidents occurring in specific provinces between two consecutive years, the framework incorporated the following equation:

$$\psi_t = \psi_{t-1}(1 - \varepsilon_{t-1}) + (1 - \psi_{t-1})\gamma_{t-1} \tag{2}$$

where

$\psi_t =$	probability of IWT activity occurring during year t
$\psi_{t-1} =$	probability of IWT activity during year $(t-1)$
$\varepsilon_{t-1} =$	probability of IWT activity discontinuing during year $(t-1)$
$\gamma_{t-1} =$	probability of IWT activity initiation during year $(t-1)$

To test various hypotheses about the spatiotemporal trends of each parameter, the framework introduces covariates to each parameter by using the following logistic regression:

$$X = \frac{e^{A+BY\ldots}}{1 + e^{A+BY\ldots}} \tag{3}$$

where

$X =$ probability of interest (ψ, ε, γ & p)
$A =$ intercept
$Y =$ covariate
$B =$ coefficient of covariate Y

Key assumptions

To build a reliable single-species, multiple-season occupancy framework, I made the following assumptions regarding my study (Bailey et al. 2013; MacKenzie et al. 2018):

1. The presence (or absence) of IWT activity at each province does not change within a year but can occur between multiple years.
2. The probabilities of the initial presence of IWT activity (ψ at year 1) and the subsequent vital rate parameters (γ, ε) are constant across all provinces; differences are modeled using covariates.
3. The probability of detecting IWT activity (p) is constant across sites and surveys; differences must be modeled using site-specific or sampling-occasion covariates.
4. IWT activity detection and detection histories (previous survey outcomes) at each province are independent.
5. IWT activities are identified correctly when present at a province; IWT activities are not falsely detected when a province is unoccupied.

METHODS

Historical poaching records

I used the Wildlife Trade Portal online database to collect reported incidents of illegal wildlife trade (IWT) activity in the Philippines from 2010-2019 (TRAFFIC International 2023). This open-access repository of wildlife seizure data was developed by TRAFFIC, an international organization that monitors the illegal trade of wild animals and plants. It is an interactive tool that displays TRAFFIC's open-source wildlife seizure and incident data, allowing users to search and filter the database. The portal provides detailed information about specific incidents, including the species, commodities, and locations involved. To identify relevant IWT incidents for this study, I set "Philippines" as the Countries search criteria and limited the search to incidents reported between "01/01/2010" and "12/31/2019." These search criteria generated 240 reported incidents of seizures, poaching/illegal harvesting, and smuggling/illegal trade of wildlife parts. I created a data matrix using Microsoft Excel with 1s and 0s denoting detection and non-detection, respectively, of one or more reported IWT incidents in each province (81 rows) during a given annual quarter (Q_1 = Jan-Mar, Q_2 = Apr-Jun, Q_3 = Jul-Sep, Q_4 = Oct-Dec) for each year between 2010 and 2019 (40 columns).

Covariates

To understand the effects of physical and socioeconomic factors on the occurrence and dynamics of IWT incidents across the Philippines, I considered variables that spatially and thematically represent the main hypotheses to be tested (Table 1).

Table 1. Hypotheses and a priori predictions about the influence of spatial and thematic variables on the occupancy (ψ), initiation (γ), discontinuation (ε), and detection (p) of reported IWT incidents in the Philippines. Variables used for each prediction are in italics.

Hypotheses and justification	Variables	Predictions
Accessibility and target richness		
Based on crime pattern theory, the occurrence of IWT incidents should cluster in and around spaces of high road density since those networks provide offenders	To represent accessibility, I built one variable as a proxy for measuring how easily humans can access previously isolated harvesting sites:	The occupancy and initiation of reported IWT incidents will be positively related to road density (*rd_dens*) and negatively related to the proportion of KBAs (*KBA*).

with higher concentrations of nodes and paths that facilitate mobility (Kurland et al. 2018). However, accessibility alone cannot fully explain the likelihood of IWT incidents. Kurland et al. (2018) suggest that the target richness must be considered in combination with accessibility to better understand where IWT incidents are more likely to occur.	1. *rd_dens*: a site-specific variable built by calculating the weighted density of road lengths (primary roads have greater weight) for each province using a GIS framework (Geofabrik GmbH 2018). To represent target richness, I built a variable that incorporates the concept of key biodiversity areas (KBAs), defined as areas supporting populations of vulnerable and irreplaceable species (Eken et al. 2004): 2. *KBA*: a site-specific variable built by calculating the proportion of KBAs within each province using a GIS framework (BirdLife International 2022). Given the archipelago's high rate of endemism, we can assume that most illegally harvested species in the Philippines are deemed vulnerable and irreplaceable (Scheffers et al. 2012). Thus, the proportion of KBAs can be a feasible proxy for estimating the likelihood that a province will have a natural supply of species targeted by IWT activity.	The discontinuation of reported IWT incidents will be negatively related to *rd_dens* and positively related to *KBA*.
Principle of least effort		
According to rational choice theory, criminals tend to choose targets in close proximity to places where stolen goods can be sold. This reduces the risks and efforts for the offenders while increasing	To test the principle of least effort in an IWT context, I built three alternate variants of variables that represent proxies for measuring the cost of performing IWT activity, specifically the cost of transporting	The occupancy and initiation of reported IWT incidents will be negatively related to the distance between KBAs and market centers (*dist_mrkt*), airports (*dist_aprt*), and seaports (*dist_sprt*).

the rewards of the crime. Thus, offenders face less risk when there are nearby secondary markets to dispose of stolen products, as this requires less travel time and lessens their likelihood of being detected or arrested (Pires and Guerette 2014). When attempting to export illicit goods to international markets, collusion, corruption, and protection amongst operatives, regulators, and law enforcers can allow organized crime to thrive at trade bottlenecks such as airports, and seaports, facilitating IWT activity (Zain 2020). For example, IWT in the Philippines frequently involves traders shipping contraband through airports without needing to hide the illicit goods or present necessary permits (Sy 2018). In the context of this study, I expect that there will be an increase in the odds of an area experiencing IWT incidents as the propinquity between KBAs and market centers, airports, and seaports increases.	illegally harvested wildlife from their natural source to domestic and international markets: 3.a. *dist_mrkt*: a site-specific variable built by calculating the minimum surface distance between a KBA boundary and the nearest market center for each province using a GIS framework (BirdLife International 2022, Geofabrik GmbH 2018). 3.b. *dist_aprt*: a site-specific variable built by calculating the minimum surface distance between a KBA boundary and the nearest airport for each province using a GIS framework (BirdLife International 2022, Geofabrik GmbH 2018). 3.c. *dist_sprt*: a site-specific variable built by calculating the minimum surface distance between a KBA boundary and the nearest seaport for each province using a GIS framework (BirdLife International 2022, Geoportal Philippines 2023).	The discontinuation of reported IWT incidents will be positively related to *dist_mrkt*, *dist_aprt*, and *dist_sprt*.
Quality of life		
Deforestation and infrastructure development have brought people and wildlife closer together, which combined with rapid population growth and urban expansion, can	To determine if social indicators motivate IWT dynamics, I built three variables as proxies representing temporal trends in the quality of life for each province:	The occupancy and initiation of reported IWT incidents will be positively related to the province's human population density (*pop_dens*), poverty incidence

increase the likelihood of wildlife exploitation, transportation and access (Gluszek et al. 2020). Poverty is another factor that can drive people in developing nations to engage in wildlife crime. Due to a lack of legitimate market opportunities in developing nations and the rising global demand for illegal wildlife products, engagement in wildlife crime can provide economic support. Therefore, poverty can directly impact the dynamics of IWT incidents (Anagnostou et al. 2021). Crime rate can also influence the pattern of IWT activities. According to convergence theory, IWT as a transnational organized crime system will have many actors across its supply chain who can form alliances and share knowledge, enabling other possible criminal activities such as robbery, assault, criminal violence, money laundering, and other forms of commodity trafficking (Anagnostou 2021). Given these social indicators, I expect IWT activity to occur more frequently in provinces with higher population density, poverty incidence, and crime rates.

4. *pop_dens*: a sampling-occasion variable built by tabulating annual (2010-2019) population densities (population/km^2) for each province based on 2010, 2015, and 2020 census data (Philippine Institute for Development Studies 2021). To estimate intercensal annual densities for each province, I extrapolated intercensal population sizes by means of arithmetic rates between two census data points (United Nations 1952).

2. *pov_incd*: a sampling-occasion variable built by tabulating the annual (2010-2019) poverty incidences (proportion of individuals with per capita income/expenditure less than the per capita poverty threshold to the total number of individuals) for each province based on 2009, 2012, 2015, 2018, and 2021 Family Income and Expenditure Survey data (Philippine Institute for Development Studies 2022). To estimate unknown annual percentages, I extrapolated values by assuming a constant rate between two survey data points.

3. *crm_rate*: a sampling-occasion variable built by tabulating the annual (2010-2019) mean crime rate (number of crimes per 100,000 individuals) for each province. To estimate the annual number of crimes for each province from regional data, I multiplied the (*pov_incd*), and crime rate (*crm_rate*) over time.

The discontinuation of reported IWT incidents will be negatively related to *pop_dens*, *pov_incd*, and *crm_rate*.

		population proportion of each province (relative to the respective regional population size) by the annual mean of regional crime incidents (Philippine Institute for Development Studies).

I quantified all spatial variables using ArcGIS Pro 3.0.3 (ESRI 2022). To organize all spatial and thematic values into their respective administrative unit, I used a shapefile delineating the boundaries of the Philippines' 81 provinces (GADM 2022). Due to the inherent limitations of occupancy models in handling missing data, I excluded provinces with missing variable values from the following model fitting steps, resulting in a final dataset of 77 provinces. I tested for collinearity among the variables with Spearman correlations using R 4.2.2 (R Development Core Team 2022) (Table 2).

Table 2. Spearman correlation matrix of the spatial and thematic variables used in the occupancy modelling of IWT activity across the Philippines relative to each province.

	rd_dens	KBA	dist_mrkt	dist_aprt	dist_sprt	pop_dens	pov_incd
KBA	– 0.44						
dist_mrkt	– 0.21	– 0.06					
dist_aprt	0.05	– 0.14	0.31				
dist_sprt	– 0.42	0.09	0.36	0.21			
pop_dens	* 0.72	– 0.46	– 0.26	– 0.21	– 0.35		
pov_incd	– 0.59	0.21	– 0.10	– 0.13	0.30	– 0.33	
crm_rate	0.32	– 0.24	0.03	0.39	0.00	0.07	– 0.05

Covariates include: road density (rd_dens), proportion of key biodiversity areas (KBA), minimum distance between a KBA and the closest market (dist_mrkt), minimum distance between a KBA and the closest airport (dist_aprt), minimum distance between a KBA and the closest seaport (dist_sprt), annual human population density (pop_dens), annual poverty incidence (pov_incd), and annual crime rate (crm_rate).

* $r > 0.70$ denotes high correlation between two variables

Model fitting and comparison

I used the package 'unmarked' in R to build a single-species multi-season occupancy framework given the restated definitions in equations (1) and (2) (Fiske & Chandler 2011). To reduce the number of models to be compared, I used a stepwise procedure adapted from Button et al. (2019). I used the package 'AICcmodavg' in R to select in each step the best-performing model based on Akaike's Information Criterion (AIC) (Akaike 1998, Mazerolle 2023). During the first step, I assessed which least effort distance ("dist_") variables (Table 1) had the highest influence on the probability of IWT activity. Also, given that "rd_dens" was highly correlated with "pd_dens" ($r > 0.70$; Table 2), I avoided combining these variables into the same parameter. I built all potential full models that included only one of the alternatives of the distance variables and one of the correlated variables, keeping fixed the variables of ψ, γ, ε, and p with no alternatives ("KBA", "pov_incd", and "crm_rate"). During the second step, I analyzed the effect of variables that may affect p by building and comparing all possible combinations of the correlated variable selected in the previous step and the three variables with no alternatives while holding all other parameters constant. During the third step, I modelled all the possible combinations of variables that can affect ψ (the two variables selected in the first step plus "KBA", "pov_incd", and "crm_rate"), keeping fixed the variables affecting p selected in the second step and holding the parameters γ and ε constant. During the fourth step, I modelled all the possible combinations of variables that can affect γ and ε (the two variables selected in the first step plus "KBA", "pov_incd", and "crm_rate"), keeping fixed the variables affecting p and ψ selected in the previous steps and holding either γ, ε, or neither parameter constant. Finally, I selected from each of the previous steps the top models with $\Delta\text{AIC} \leq 3$ and ran a final multi-model comparison (Table 3).

Estimating covariate relationships

From the top-ranking multi-season model, I used the package 'unmarked' in R 4.2.2 (Fiske & Chandler) to generate a list of β-coefficient estimates of each covariate included in the top model (Table 4). I selected the best supported covariates ($p < 0.05$; 95% CI does not contain 0) and plotted the predicted relationship between the covariate and its associated parameter in R 4.2.2. I accounted for model uncertainty by displaying the 95% confidence interval onto the prediction plot (Figure 2).

Predicting the spatial distribution of IWT activity

To predict the spatial distribution of potential IWT activity across all provinces in the Philippines, I used the *predict* function in the R 4.2.2 'base' package (R Development Core Team 2022) to derive occupancy (ψ) estimates from the top-ranking multi-season model. For each province, I calculated standard errors of occupancy estimates using the *nonparboot* function in the 'unmarked' R package, running at 100 bootstrap samples (Fiske & Chandler 2011). To map the predicted levels of IWT activity in each province, I used ArcGIS Pro 3.0.3 (ESRI 2022) and extrapolated the occupancy estimates onto the entire study area of the Philippines (Figure 3).

RESULTS

Model selection

In total, I developed 182 models using a stepwise procedure. My top-ranked model included the proportion of KBAs, annual poverty incidence, and annual crime rate as covariates for every parameter; the minimum distance between KBAs and the nearest airport as covariates for initial occupancy, initiation, and discontinuation; road density as covariates for initial occupancy and detection; and human population density as covariates for initiation and discontinuation (Table 3).

Covariate relationships

The probability of IWT activity initiating in a province without on-going IWT activity (γ) decreased as the distance between a KBA and the nearest airport increases (Table 4; Figure 2a; $\beta = -0.130$; 95% CI: -0.242, -0.019), and the same probability increases as the log of human population density increases (Table 4; Figure 2b; $\beta = 2.767$; 95% CI: 0.797, 4.763). The probability of detecting IWT activity within a province (p) increases as road density increases

(Table 4; Figure 2c; $\beta = 0.190$; 95% CI: 0.121, 0.260) and the same probability increases as the proportion of KBAs within a province increases (Table 4; Figure 2d; $\beta = 4.276$; 95% CI: 3.295, 5.256). All other covariates had negligible influence on the four parameters.

Table 3. Topmost multi-season models built using a stepwise procedure (Button et al. 2019) and ranked by AIC. Models from each step with $\Delta\text{AIC} \leq 3$ were selected for a final multi-model comparison and ranked by AIC. Models are used to estimate probabilities of IWT activity in the Philippines occurring within a province (ψ), initiating into a province without on-going IWT activity (γ), discontinuing from a province with on-going IWT activity (ε), and probability of detecting IWT activity in a province (p).

Model	AIC	ΔAIC	w	K
ψ(rd_dens + KBA + dist_aprt + pov_incd + crm_rate), γ(KBA + dist_arprt + pop_dens + pov_incd + crm_rate), ε(KBA + dist_arprt + pop_dens + pov_incd + crm_rate), p(rd_dens + KBA + pov_incd + crm_rate)	1129.41	0.00	0.82	23
ψ(KBA + dist_arprt + pop_dens + pov_incd + crm_rate), γ(KBA + dist_arprt + pop_dens + pov_incd + crm_rate), ε(KBA + dist_arprt + pop_dens + pov_incd + crm_rate), p(rd_dens + KBA + pov_incd + crm_rate)	1132.41	3.00	0.18	23
ψ(rd_dens + dist_arprt + crm_rate), γ(.), ε(rd_dens + KBA + dist_arprt + pov_incd), p(rd_dens + pov_incd)	1159.59	30.19	< 0.00	13
ψ(rd_dens + dist_arprt + crm_rate), γ(.), ε(.), p(rd_dens + pov_incd)	1174.33	44.93	< 0.00	8
ψ(dist_arprt + crm_rate), γ(.), ε(.), p(rd_dens + pov_incd)	1176.02	46.61	< 0.00	8
ψ(rd_dens + KBA + dist_arprt + crm_rate), γ(.), ε(.), p(rd_dens + pov_incd)	1176.08	46.67	< 0.00	10
ψ(.), γ(.), ε(.), p(rd_dens + pov_incd)	1177.87	48.46	< 0.00	6
ψ(.), γ(.), ε(.), p(rd_dens + pov_incd + crm_rate)	1178.32	48.91	< 0.00	7
ψ(.), γ(.), ε(.), p(pov_incd + crm_rate)	1178.91	49.50	< 0.00	6
ψ(.), γ(.), ε(.), p(rd_dens)	1180.27	50.86	< 0.00	5

Presented in the table are differences in AIC values between the respective models and the top model (ΔAIC), AIC weight (w), and number of parameters (K).
Covariates include: road density (rd_dens), proportion of key biodiversity areas (KBA), minimum distance between a KBA and the closest market (dist_mrkt), minimum distance between a KBA and the closest airport (dist_aprt), minimum distance between a KBA and the closest seaport (dist_sprt), annual human population density (pop_dens), annual poverty incidence (pov_incd), and annual crime rate (crm_rate). A single period (.) denotes a constant probability of the corresponding parameter.

Table 4. Estimates of *beta*-coefficients (β) and standard errors (Std. Err.) of covariates for the top scoring multi-season model.

Parameter	Covariate	β	Std. Err.
ψ	rd_dens	2.072	1.351
	KBA	– 5.005	3.158
	dist_arprt	– 0.076	0.052
	pov_incd	0.024	0.042
	cr_rate	0.199	0.151
γ	KBA	2.496	1.627
	dist_arprt *	– 0.130	0.057
	pop_dens **	2.767	1.004
	pov_incd	0.017	0.018
	cr_rate	0.093	0.072
ε	KBA	7.256	4.763
	dist_arprt	– 0.193	0.067
	pop_dens	5.315	3.262
	pov_incd	0.029	0.057
	cr_rate	– 0.347	0.205
p	rd_dens ***	0.190	0.035
	KBA ***	4.276	0.500
	pov_incd	– 0.004	0.008
	cr_rate	– 0.003	0.009

Covariates include: road density (rd_dens), proportion of key biodiversity areas (KBA), minimum distance between a KBA and the closest market (dist_mrkt), minimum distance between a KBA and the closest airport (dist_aprt), minimum distance between a KBA and the closest seaport (dist_sprt), annual human population density (pop_dens), annual poverty incidence (pov_incd), and annual crime rate (crm_rate).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

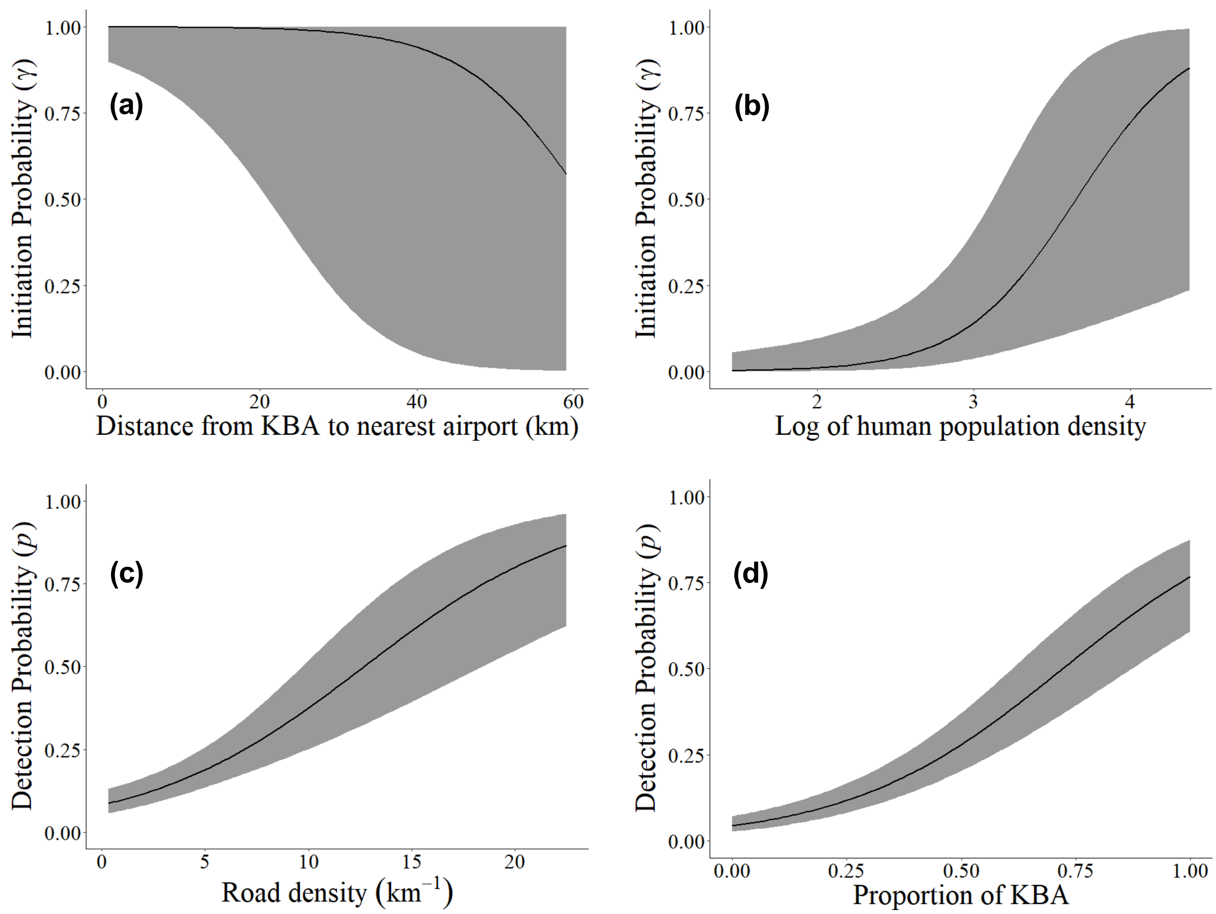

Figure 2. Probability of IWT activity initiating into a Philippine province without on-going IWT activity as a function of the minimum distance between a KBA and the nearest airport (a) or the log of human population density of each province. Probability of detecting IWT activity within a Philippine province as a function of road density or proportion of key biodiversity areas (KBA) of each province (d). Shaded areas represent 95% CI. Estimates are from the top scoring multi-season model.

Spatial distribution of IWT activity

The central and interior islands of the Philippine archipelago exhibited a higher predicted probability of IWT activity (Figure 3). A concentrated area of southwestern Luzon, extending from the capital Manila to the surrounding provinces, showed a pronounced concentration of high IWT probability (Figure 3). Among the 77 provinces included in our analysis, 22.1% displayed low IWT activity ($\psi \leq 0.33$), 18.2% exhibited medium IWT activity ($0.34 \leq \psi \leq 0.67$), and 59.7% demonstrated high IWT activity ($\psi \geq 0.68$).

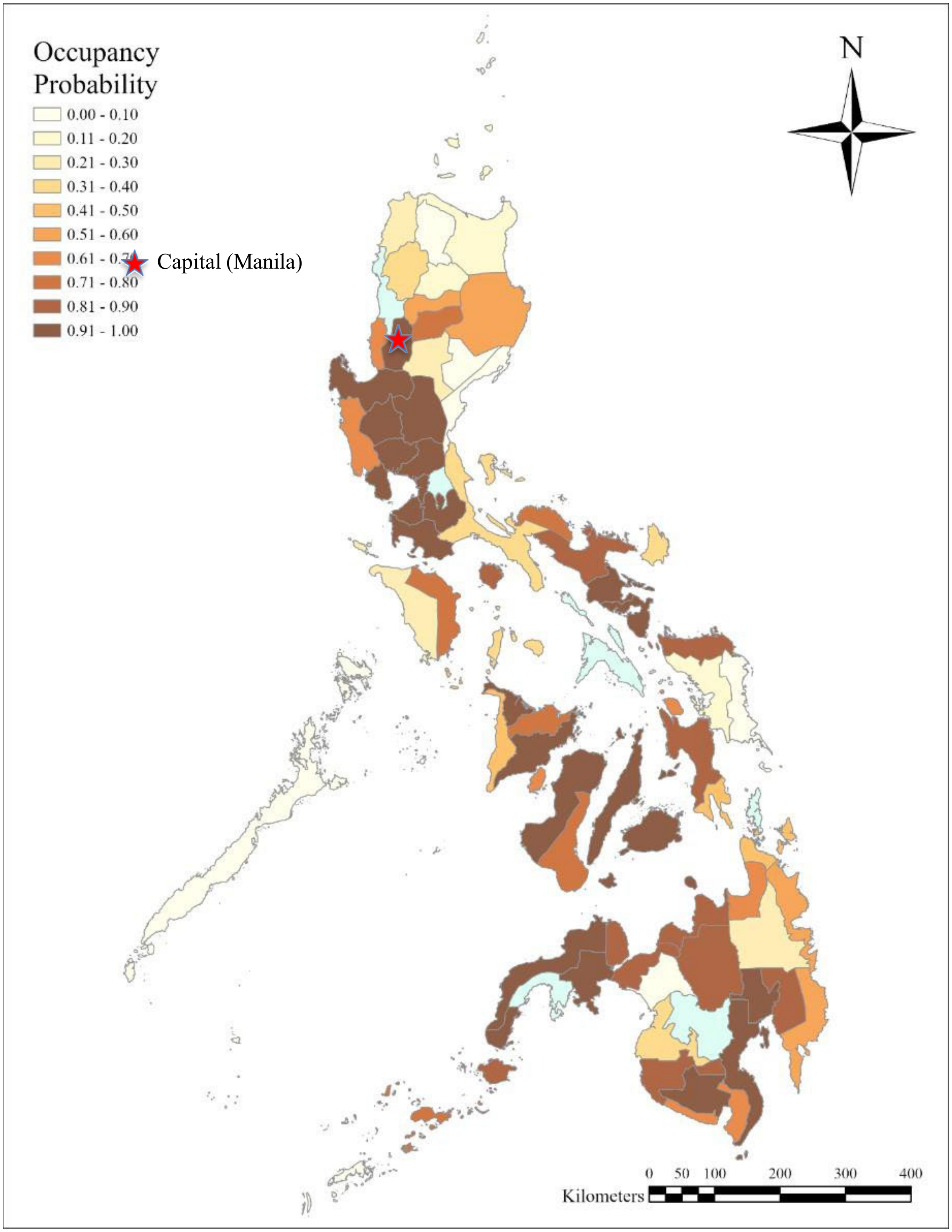

Figure 3. The predicted probabilities of occurrence of IWT activity (ψ) across 77 provinces in the Philippines derived from the top scoring multi-season model. Lines represent the administrative boundaries of each province. Light blue areas represent provinces excluded from models analysis.

DISCUSSION

The models ranking highest were comprehensive models encapsulating numerous covariates for each parameter (Table 3). This outcome underscores the complexity inherent in the study of IWT activity, highlighting its dependence on, and susceptibility to, a multiplicity of factors and variables. Notably, our top-performing model was effectively a comprehensive model that included determinants spanning all three categories of hypotheses: accessibility and target richness, least cost effort, and quality of life. This indicates that these categories collectively exert a significant influence on the dynamics of IWT activity.

Accessibility and target richness

My findings reveal a significant positive relationship between road density and the likelihood of detecting IWT activity (Figure 2c), emphasizing the role of accessibility in such scenarios. Notably, provinces with higher road density, which indicates better accessibility, facilitate more efficient patrolling and faster response to incidents by law enforcement agencies (Brantingham and Brantingham 1993). Moreover, these areas offer more opportunities for law enforcement patrols, thereby increasing police visibility and potentially deterring IWT activities. This association is consistent with the Crime Pattern Theory, suggesting that the geographical distribution of crimes is influenced by the interplay between suitable targets, motivated offenders, and the absence or presence of capable guardians (Brantingham and Brantingham 1993). In our context, road density can affect the movement patterns of both offenders and law enforcement, thereby impacting the likelihood of crime detection.

In terms of target richness, the proportion of KBAs was found to have a positive relationship with the probability of detecting IWT activity (Figure 2d). This suggests that provinces with a higher biodiversity and species richness attract more resources for anti-IWT efforts. Resource-rich areas are often the focus of significant economic activity, particularly the exploitation of wildlife, which necessitates an increased law enforcement presence and resource allocation to protect and monitor these regions (Esmail et al. 2019). Furthermore, due to the economic and environmental implications of natural resource extraction, stricter regulatory oversight is often imposed by governments and regulatory bodies. This enhanced regulatory oversight, involving inspections, audits, and reporting requirements, can increase the chances of detecting illegal activities (Ayling 2013).

Least cost effort

Within the context of a least cost effort analysis, the primary determinant was the minimum distance between a KBA and the nearest airport (Table 3). This variable remained salient even when we incorporated alternative transit and destination points into our analysis (i.e., markets and seaports). The weight of the variable relating to airports as transit points indicates a strong preference among distributors of illicit wildlife products for this type of transportation hub. This, in turn, implies the presence of a significant international market that is driving IWT activity.

Moreover, we found a strong inverse correlation between the probability of initiating IWT activity and the proximity of a KBA to the nearest airport (Figure 2a). This finding suggests that new IWT activity tends to originate more frequently in locations where the transportation of wildlife products to an airport is relatively uncomplicated. These conclusions align with the existing literature, which indicates that organized criminal groups involved in wildlife crime frequently leverage sophisticated and complex transportation and financial networks (Keskin et al. 2023). Such networks, often characterized by intricate supply chains, are typically centered around established transportation channels, including passenger air travel.

Quality of life

Our findings strongly indicate that in terms of a province's quality of life, the primary determinant is human population density, particularly its positive correlation to the initiation of IWT in provinces with ongoing IWT activities (Figure 2b). This relationship suggests a higher population density likely presents increased opportunities and prospects for individuals to partake in IWT activities within a given province. Interestingly, our study found that poverty incidence did not significantly correlate with IWT occupancy dynamics. Conventional understanding might suggest that poverty could be a driving force behind IWT activity due to the potential for increased income (Roe 2008). However, our data indicates that poverty does not necessarily initiate poaching or IWT activities. A key factor to consider is that individuals are unlikely to engage in IWT activities unless there is a demand from wealthier communities. A report from TRAFFIC provides an additional perspective, suggesting that new drivers of the illegal wildlife trade are emerging, shifting from traditional culture-related consumption to new forms of conspicuous consumption driven by rising incomes (Milliken and Shaw 2012).

Limitations and future directions

This study encountered several limitations that merit further discussion. Firstly, the scarcity of data on IWT networks presents a significant constraint, largely owing to their clandestine and illicit nature, making it challenging to discern the true extent of IWT. The primary source of IWT data stems from seizure records generated by successful interdiction activities, which inherently introduces bias (Keskin et al. 2023). These biases might manifest in multiple forms, such as centralized datasets not encapsulating the complete range of wildlife trade, or simply the absence of data due to undetected wildlife trade. For example, our reliance on seizure data may skew the focus towards regions already investing in IWT interdiction, potentially neglecting other regions requiring attention (Keskin et al. 2023).

Furthermore, our study did not entirely account for the varying levels of patrol or reporting effort across different provinces over time. The potential discrepancies in police or ranger efforts across different regions and timelines present an additional layer of complexity. Lastly, it is critical to recognize that the decision to participate in IWT is shaped by an individual's social, political, and economic context. Economic considerations, social-psychological factors, and societal norms and expectations influence these decisions (Duffy and St. John 2013). Therefore, a more nuanced understanding of these relationships is essential for effectively addressing IWT. Future research should strive to delve deeper into these aspects to provide a more comprehensive picture of the issue at hand.

Conclusion

This study offers notable contributions to our understanding of the illegal wildlife trade landscape and provides tangible strategies for mitigating its effects. Foremost, the methods, tools, and insights derived from this analysis can guide the deployment of crime forecasting models to better predict, prevent, and combat IWT. Furthermore, the results underscore the potential impact of alternative livelihood programs, conservation education, and advocacy in reshaping perceptions and attitudes towards wildlife and its conservation, highlighting the potential for transformative change at the individual and community level. Simultaneously, my research broadens the understanding of the various physical and socioeconomic factors that drive, facilitate, and motivate IWT networks and activity. The study encourages a reevaluation of conventional views on IWT, specifically the correlation between an individual's socioeconomic status and participation in such activities. Importantly, the research also necessitates a shift in focus from the supply to the demand side of the IWT equation. Recognizing that the market demand for IWT products is a primary driver behind these activities is critical for the development of effective intervention strategies. In essence, this study contributes significantly to the ongoing discourse on IWT, providing a comprehensive framework for understanding and combatting this complex issue. Future work should continue to explore and refine these strategies, focusing on both prevention and intervention, for a more holistic and effective response to IWT.

ACKNOWLEDGEMENTS

I would like to thank my mentor, Dr. Thomas Connor from the Brashares and Middleton labs. I would also like to thank the ESPM 175 team: Dr. Patina Mendez, Danielle Perryman, and Robin Lopez. Finally, I want to thank Michael Virtucio for obtaining seizure data from the Philippines' Department of Natural Resources, and Maura Lievano for providing me with criminology and data analysis resources.

REFERENCES

Akaike, H. 1998. Information Theory and an Extension of the Maximum Likelihood Principle. Pages 199–213 *in* E. Parzen, K. Tanabe, and G. Kitagawa, editors. Selected Papers of Hirotugu Akaike. Springer New York, New York, NY.

Anagnostou, M. 2021. Synthesizing knowledge on crime convergence and the illegal wildlife trade. Environmental Challenges 5:100222.

Anagnostou, M., W. D. Moreto, C. J. Gardner, and B. Doberstein. 2021. Poverty, Pandemics, and Wildlife Crime. Conservation and Society 19:294.

Ayling, J. 2013. What Sustains Wildlife Crime? Rhino Horn Trading and the Resilience of Criminal Networks. Journal of International Wildlife Law & Policy 16:57–80.

Bailey, L. L., D. I. MacKenzie, and J. D. Nichols. 2014. Advances and applications of occupancy models. Methods in Ecology and Evolution 5:1269–1279.

Beerepoot, N. 2018. The Philippine Archipelago. YvesBoquet, Berlin, 2017, 848 pp, Springer International Publishing. ISBN 978-3-319-5925-8, €212 hb. Tijdschrift voor economische en sociale geografie 109:327–328.

Benítez-López, A., R. Alkemade, A. M. Schipper, D. J. Ingram, P. A. Verweij, J. A. J. Eikelboom, and M. A. J. Huijbregts. 2017. The impact of hunting on tropical mammal and bird populations. Science 356:180–183.

BirdLife International. 2022. The World Database of Key Biodiversity Areas.

BMB-DENR, Biodiversity Management Bureau, Department of Environment and Natural Resources. 2016. Philippine Biodiversity Strategy and Action Plan (2015-2028): Bringing Resilience to Filipino Communities.

Brantingham, P. L., and P. J. Brantingham. 1993. Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. Journal of Environmental Psychology 13:3–28.

Button, S. T., A. R. Sovie, C. H. Greenberg, and J. D. Austin. 2019. Evaluating the Ecology of Tantilla relicta in Florida Pine–Wiregrass Sandhills Using Multi-Season Occupancy Models. Journal of Herpetology 53:179.

Corlett, R. T. 2007. The Impact of Hunting on the Mammalian Fauna of Tropical Asian Forests. Biotropica 39:292–303.

Eken, G., L. Bennun, T. M. Brooks, W. Darwall, L. D. C. Fishpool, M. Foster, D. Knox, P. Langhammer, P. Matiku, E. Radford, P. Salaman, W. Sechrest, M. L. Smith, S. Spector, and A. Tordoff. 2004. Key Biodiversity Areas as Site Conservation Targets. BioScience 54:1110–1118.

Esmail, N., B. C. Wintle, M. t Sas-Rolfes, A. Athanas, C. M. Beale, Z. Bending, R. Dai, M. Fabinyi, S. Gluszek, C. Haenlein, L. A. Harrington, A. Hinsley, K. Kariuki, J. Lam, M. Markus, K. Paudel, S. Shukhova, W. J. Sutherland, D. Verissimo, Y. Wang, J. Waugh, J. H. Wetton, C. Workman, J. Wright, and E. J. Milner-Gulland. 2020. Emerging illegal wildlife trade issues: A global horizon scan. Conservation Letters 13:e12715.

ESRI. 2022. ArcGIS Pro 3.0.3.

Fischer, C. 2021. Illegal Wildlife Trade at the Philippine-Southeast Asian Nexus: An Assessment of Projects combating Illegal Wildlife Trade in Southeast Asia informing the Philippines and guiding Donor Coordination.

Fiske, I., and R. Chandler. 2011. **unmarked** : An *R* Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance. Journal of Statistical Software 43.

GADM. 2022. Philippines Administrative Areas.

Geofabrik GmbH. 2018. OpenStreetMap data for this region: Philippines.

Geoportal Philippines. 2023. Port and Harbor Chart 2023 WGS.

Gluszek, S., D. Ariano-Sánchez, P. Cremona, A. Goyenechea, D. A. L. Vergara, L. Mcloughlin, A. Morales, A. R. Cortes, J. R. Fonseca, J. Radachowsky, and A. Knight. 2021. Emerging trends of the illegal wildlife trade in Mesoamerica. Oryx 55:708–716.

Harrison, R. D., R. Sreekar, J. F. Brodie, S. Brook, M. Luskin, H. O'Kelly, M. Rao, B. Scheffers, and N. Velho. 2016. Impacts of hunting on tropical forests in Southeast Asia: Hunting in Tropical Forests. Conservation Biology 30:972–981.

Hughes, A. C. 2017. Understanding the drivers of Southeast Asian biodiversity loss. Ecosphere 8:e01624.

Keskin, B. B., E. C. Griffin, J. O. Prell, B. Dilkina, A. Ferber, J. MacDonald, R. Hilend, S. Griffis, and M. L. Gore. 2023. Quantitative Investigation of Wildlife Trafficking Supply Chains: A Review. Omega 115:102780.

Kurland, J., S. F. Pires, and N. Marteache. 2018. The spatial pattern of redwood burl poaching and implications for prevention. Forest Policy and Economics 94:46–54.

MacKenzie, D. I. 2018. Occupancy estimation and modeling: inferring patterns and dynamics of species occurrence. Second edition. Academic Press, an imprint of Elsevier, London, United Kingdom.

Mazerolle, M. 2023. AICcmodavg: Model selection and multimodel inference based on (Q)AIC(c).

Milliken, T., and J. Shaw. 2012. The South Africa-Viet Nam rhino horn trade nexus: a deadly combination of institutional lapses, corrupt wildlife industry professionals, and Asian crime syndicates. TRAFFIC, Johannesburg, South Africa.

Moore, J. F., F. Mulindahabi, M. K. Masozera, J. D. Nichols, J. E. Hines, E. Turikunkiko, and M. K. Oli. 2018. Are ranger patrols effective in reducing poaching-related threats within protected areas? Journal of Applied Ecology 55:99–107.

Philippine Institute for Development Studies. 2019. Average Monthly Crime Rate by Region, 2009-2019, Percent. Economic and Social Database.

Philippine Institute for Development Studies. 2021. Actual Population by Province: Based on Censuses 1990 to 2020, In Person. Economic and Social Database.

Philippine Institute for Development Studies. 2022. Poverty Incidence Among Population, by Region and Province. Economic and Social Database.

Pires, S. F., and R. T. Guerette. 2014. Does opportunity make the poacher?: An analysis of neo-tropical illicit parrot markets. Page Situational Prevention of Poaching. Routledge.

R Development Core Team. 2022. R: A language and environment for statistical computing.

Roe, D. 2008. The origins and evolution of the conservation-poverty debate: a review of key literature, events and policy processes. Oryx 42:491.

Rosen, G. E., and K. F. Smith. 2010. Summarizing the Evidence on the International Trade in Illegal Wildlife. EcoHealth 7:24–32.

Scheffers, B. R., R. T. Corlett, A. Diesmos, and W. F. Laurance. 2012. Local Demand Drives a Bushmeat Industry in a Philippine Forest Preserve. Tropical Conservation Science 5:133–141.

Sy, E. Y. 2018. Trading Faces: Utilisation of Facebook to Trade Live Reptiles in the Philippines.

TRAFFIC International. 2023. Wildlife Trade Portal. https://www.wildlifetradeportal.org.

United Nations. 1952. Manuals on Methods of Estimating Population. Manual 5-Methods of Projecting the Economically Active Population.

Zain, S. 2020. Corrupting trade: An overview of corruption issues in illicit wildlife trade. https://www.worldwildlife.org/pages/tnrc-introductory-overview-corrupting-trade-an-overview-of-corruption-issues-in-illicit-wildlife-trade.