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Effects of Shifting Cultivation on the Western Hoolock Gibbon (*Hoolock hoolock*) in Western Myanmar

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ABSTRACT

Shifting cultivation is a major driver of deforestation in tropical uplands. In western Myanmar, population growth has intensified the practice, shortening fallow periods and resulting in increased habitat degradation and fragmentation, which threaten wildlife survival. Arboreal species such as gibbons are particularly vulnerable due to their reliance on continuous canopy cover for survival. We investigated how shifting cultivation and associated human disturbances affect the density and abundance of the Western hoolock gibbon (*Hoolock hoolock*) in Man Wildlife Sanctuary, a newly established protected area, and its surrounding forest landscape in western Myanmar. Data were collected using point counts at 36 sampling grids covering 113 km^2 over 8 months (April–November 2023). Density estimates were derived from abundance using N-mixture models, and we examined the influence of landscape and human disturbance covariates on spatial variation in gibbon abundance across the study area. We estimated an average density of 1.6 groups/km^2. Of the seven landscapes and eight disturbance covariates tested, fire-related disturbances and proximity to human settlements—both closely associated with shifting cultivation—had the strongest negative influence on gibbon density. Our results suggest that Man Wildlife Sanctuary and its surrounding forests support a moderate density of Western hoolock gibbons compared with other regions in Myanmar. The lack of effective protection and management is a major problem, highlighting the need for targeted conservation measures and land-use planning to mitigate these threats.

1 | Introduction

Shifting cultivation, also known as swidden agriculture, is a traditional agricultural practice widespread in tropical regions and has long been the dominant agricultural system for subsistence farmers in the mountainous areas of South and Southeast Asia (Mukul and Herbohn 2016; Thet and Tokuchi 2021). Many people in these hilly regions still depend on it, at least in part, for their livelihoods and food security. The practice begins with the clearing of forest vegetation, often using fire, followed by food crop cultivation, and then a fallow period during which the land is left to regenerate with natural vegetation (Borah et al. 2022). Traditionally, shifting cultivation was sustainable, as long fallow periods were maintained and alternative land patches were available, due to limited human population pressure (Nath et al. 2016). These periods were often followed by burning, which led to direct habitat conversion and fragmentation (Arce-Peña et al. 2019). However, with population growth, this system has become increasingly unsustainable. The shortening of fallow periods to increase productivity has been identified as a significant factor contributing to forest degradation (Tran et al. 2011), fragmentation (Arce-Peña et al. 2019), and soil deterioration

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Summary

We studied the impact of shifting cultivation and related human disturbances on the Western hoolock gibbon (*Hoolock hoolock*) in Man Wildlife Sanctuary and adjacent forests in western Myanmar. In this region, shifting cultivation is widespread and has become increasingly unsustainable, leading to significant habitat degradation and fragmentation. These changes pose a serious threat to the survival of this canopy-dependent primate. Between April and November 2023, we surveyed 36 locations across 113 km^2, both within and outside the sanctuary, to estimate gibbon density and assess the impact of environmental and anthropogenic factors on the population. We found an average gibbon density of 1.6 groups per km^2, indicating that the area supports a moderate population compared with other parts of Myanmar. Our analysis showed that gibbon density was lower in areas affected by forest fires and those located near human settlements. Conservation of this endangered species requires sustainable land-use planning, protection of remaining forest patches, restoration of canopy connectivity, and engagement with local communities to raise awareness.

- **Practitioner Points**
  - Fire disturbance and proximity to villages reduce gibbon density in shifting cultivation landscapes.
  - Protecting remaining forest patches and restoring canopy connectivity are critical for gibbon conservation.
  - Conservation efforts should integrate land-use planning and community engagement in areas surrounding the protected area.

(Chan et al. 2016). These changes pose a serious threat to biodiversity, resulting in decreased species diversity within ecosystems (Schmid et al. 2021). In addition, shifting cultivation often increases fire frequency, contributing to long-term forest structure degradation and undermining ecological integrity (Lawrence et al. 2010). Such impacts can have far-reaching consequences for wildlife populations, particularly habitat specialists like the Western hoolock gibbon (*Hoolock hoolock*), and may compromise the effectiveness of broader conservation efforts.

Shifting cultivation and other anthropogenic disturbances affect arboreal primates by changing critical aspects of forest structure. Land-use changes often lead to habitat fragmentation, reduced canopy connectivity, and spatial dispersion of food resources (Marsh et al. 2003; Arroyo-Rodríguez and Fahrig 2014). For canopy-dependent species such as the Western hoolock gibbon (*Hoolock hoolock*), these structural disruptions impair key behaviors, including foraging, territorial movement, and social interaction. Fragmented and degraded landscapes increase energetic costs, reduce access to fruiting trees, and constrain group mobility, ultimately threatening population persistence (Marshall and Leighton 2006).

Similar ecological mechanisms have been documented in other endangered primates. Changes in forest composition, connectivity, and forest cover have been linked to population declines in several species (Arce-Peña et al. 2019). These findings underscore the importance of habitat configuration in conservation planning for arboreal primates. Building on this rationale, our study examines how shifting cultivation and associated disturbances influence the distribution and abundance of the Western hoolock gibbon in a fragmented landscape in western Myanmar.

Among the species most affected by deforestation, gibbons have suffered significant population declines over the past 30–40 years (Cheyne et al. 2008; Lwin et al. 2021), primarily due to habitat degradation and fragmentation (Arroyo-Rodríguez et al. 2013). These primates rarely descend to the forest floor and require a continuous canopy for brachiation (Muzaffar et al. 2007; Chivers 2000), making them particularly sensitive to habitat changes driven by shifting cultivation (Deb et al. 2014). They have also been recognized as excellent indicators of forest health (Deb et al. 2014) and forest management quality (Lwin et al. 2022; Tun et al. 2023).

The Arakan Mountain range is a priority biodiversity corridor in Myanmar, representing the second-largest area of contiguous lowland forest in the country (Forest Department 2015). It is designated as part of the Nat-yekan Key Biodiversity Area and supports one of the few remaining viable populations of the Endangered Western hoolock gibbon (*Hoolock hoolock*) (Geissmann 2013). This region also provides critical ecosystem services as an important watershed in the Ayeyarwady River basin, supplying irrigation water to Myanmar's dry zone (Forest Department 2015; Geissmann 2013).

Despite its ecological significance, the distribution and habitat status of the Western hoolock gibbon in this region remain poorly documented. Shifting cultivation has extensively impacted the study area, yet its specific effects on habitat quality are not well understood. In particular, the influence of this agricultural practice on species that require continuous forest cover, such as gibbons, has not been thoroughly investigated, emphasizing the need for targeted studies. Man Wildlife Sanctuary, designated as a protected area by the Forest Department in 2021, forms part of the Nat-Yekan Key Biodiversity Area (Critical Ecosystem Partnership Fund 2012). It provides habitat for at least 12 threatened mammal species, including the Western hoolock gibbon. However, forest degradation and fragmentation persist due to shifting cultivation and the collection of non-timber forest products. Given the high biodiversity value, urgent conservation and management actions are needed, particularly in light of the infrastructure deficit and the lack of permanent staff needed for protected area management. Given the time and financial constraints and the urgency of initiating conservation measures, surveys should prioritize indicator species such as the Western hoolock gibbon.

This study, therefore, investigates the impact of shifting cultivation on the population density of the Western hoolock gibbon and proposes conservation strategies to mitigate the negative effects of habitat fragmentation and degradation on gibbon populations. Specifically, we aim to: (1) estimate the population abundance and density of the Western hoolock gibbon in Man Wildlife Sanctuary using N-mixture models; (2) determine the effect of shifting cultivation on gibbon abundance; and (3) identify priority areas for improved conservation management within the study area. We hypothesize that shifting cultivation negatively affects gibbon population density, particularly through fire-related disturbances and increased proximity to human settlements. Our findings will contribute to an increased understanding of how shifting cultivation influences habitat quality in Western hoolock gibbon landscapes and will inform conservation planning and sustainable village land-use policies that balance human livelihoods with biodiversity conservation.

2 | Materials and Methods

2.1 | Study Site

The study was conducted in the Man Wildlife Sanctuary and its surrounding forest landscape (19°48′ to 20°08′ N, 94°10′ to 94°23′ E), located in the Chin Hills–Arakan Yoma Mountain Range Forest ecoregion in western Myanmar (Wikramanayake et al. 2002; Figure 1). The sanctuary covers approximately 124 km^2, with elevations ranging from 308 m to just over 1,700 m above sea level. The forest ridges within the sanctuary are dominated by primary evergreen forest, with only a small portion converted to shifting cultivation. In contrast, the surrounding forest landscape (approximately 350 km^2, elevation range 265–1696 m) is more heavily influenced by human activity, characterized by widespread shifting cultivation, bamboo scrub, regenerating forest, and upland agricultural fields.

The average temperature is 29°C during the hottest months (March–May) and 20°C in the coldest months (December–January). Annual rainfall ranges from 1742 to 2243 mm (Funk et al. 2015). There are 11 villages located in the study area, most established between 1904 and 1920. The majority of residents belong to the Asho Chin ethnic group and rely primarily on hillside agriculture, particularly shifting cultivation of rice and vegetables for subsistence. Non-timber forest products also play an important role in their livelihoods. Increasing human population pressure has shortened shifting cultivation cycles and expanded cultivation into the remaining primary forest areas, creating a fragmented landscape of cultivation fields and secondary vegetation at various successional stages.

2.2 | Gibbon Density Estimates

2.2.1 | Survey Design

Gibbon group abundance was estimated using auditory point count surveys (Lwin et al. 2022). Data were collected over 114 days between April and November 2023, across 36 sampling grids. The study area was divided into 36 grid squares (2.5 km × 2.5 km, 6.25 km^2 each), located both within and adjacent to the sanctuary. Each sampling grid contained two listening points (72 in total) placed 450–600 m apart, ideally on ridges or other high-elevation locations near the grid center to maximize detectability. To ensure independence between adjacent locations, we maintained a minimum distance of 1000 m between listening locations at each grid, eliminating overlap in detection fields.

The survey covered three distinct habitat types: primary forest (9 grids), secondary forest (9 grids), and shifting cultivation areas (18 grids). The two listening points within each grid were surveyed simultaneously over four consecutive days between 06:00 and 12:00.

2.2.2 | Group Identification

At each listening point, we recorded the bearing, distance, start and end times, and song type (duet or solo) of gibbon calls. We then used triangulation to determine gibbon group locations based on the intersection of bearings from two fixed points (Lwin et al. 2022). Locations of calling groups were mapped for each session using triangulation based on the angles and timing of the duet bouts heard (Lwin et al. 2022). Groups were considered distinct if calls originated more than 500 m apart on the triangulation map. If song bouts overlapped in time but locations were within 500 m, they were still counted as different groups (Lwin et al. 2022). Habitat characteristics and weather conditions were also recorded (Syxaiyakhamthor et al. 2020).

In our study area, duets occurred between 06:20 and 11:48, with most calls (52.4%) starting before 09:00: 8.3% between 06:00–07:00, 18.6% between 07:00–08:00, 25.9% between 08:00–09:00, 19.7% between 09:00–10:00, and 27.6% after 10:00 ($n = 491$ calls). The mean call duration was 20 min (range: 3–45 min).

2.2.3 | Density Estimation

To calculate gibbon density, we defined the effective listening area within each grid as a circle with a 1 km radius (3.14 km^2) centered between the two listening points. All group detections were mapped relative to this point. Because gibbons do not duet daily and their vocalizations can be influenced by weather (Cheyne et al. 2008; Syxaiyakhamthor et al. 2020), we recorded weather conditions (cloudy and sunny) as a detection covariate in analyses.

2.3 | *Selection* and Acquisition of Landscape and Human Disturbance Variables

To model gibbon abundance and density, we defined seven landscape variables and eight human disturbance variables, all measured within a 1 km buffer around each grid center using ArcGIS 10.8 (see Table 1 for more details). Landscape variables were (1) elevation, (2) ruggedness (defined as the standard deviation of elevation), (3) area of primary forest, (4) area of secondary forest, (5) Normalized Difference Vegetation Index (NDVI), (6) Canopy Height, and (7) Canopy Cover. Mean elevation was calculated using Digital Elevation Models (DEMs) sourced from the 30 m SRTM Tile Downloader (https://wtkns.com/srtm30m). Primary and secondary forests were derived from the Harmonized Sentinel-2 MSI data set using a supervised classification method in Google Earth Engine (https://developers.google.com/ earth-engine/datasets/catalog/COPERNICUS_S2_SR_HARMONIZED). NDVI values were derived from the Sentinel-2 Harmonized Level-2A data set. Canopy Height data was sourced from https://gee-community-catalog.org/projects/meta_trees/ (Tolan et al. 2024). Canopy cover data was sourced from COPERNICUS/Landcover/100 m/Proba-V-C3/Global/2019 (Buchhorn et al. 2020).

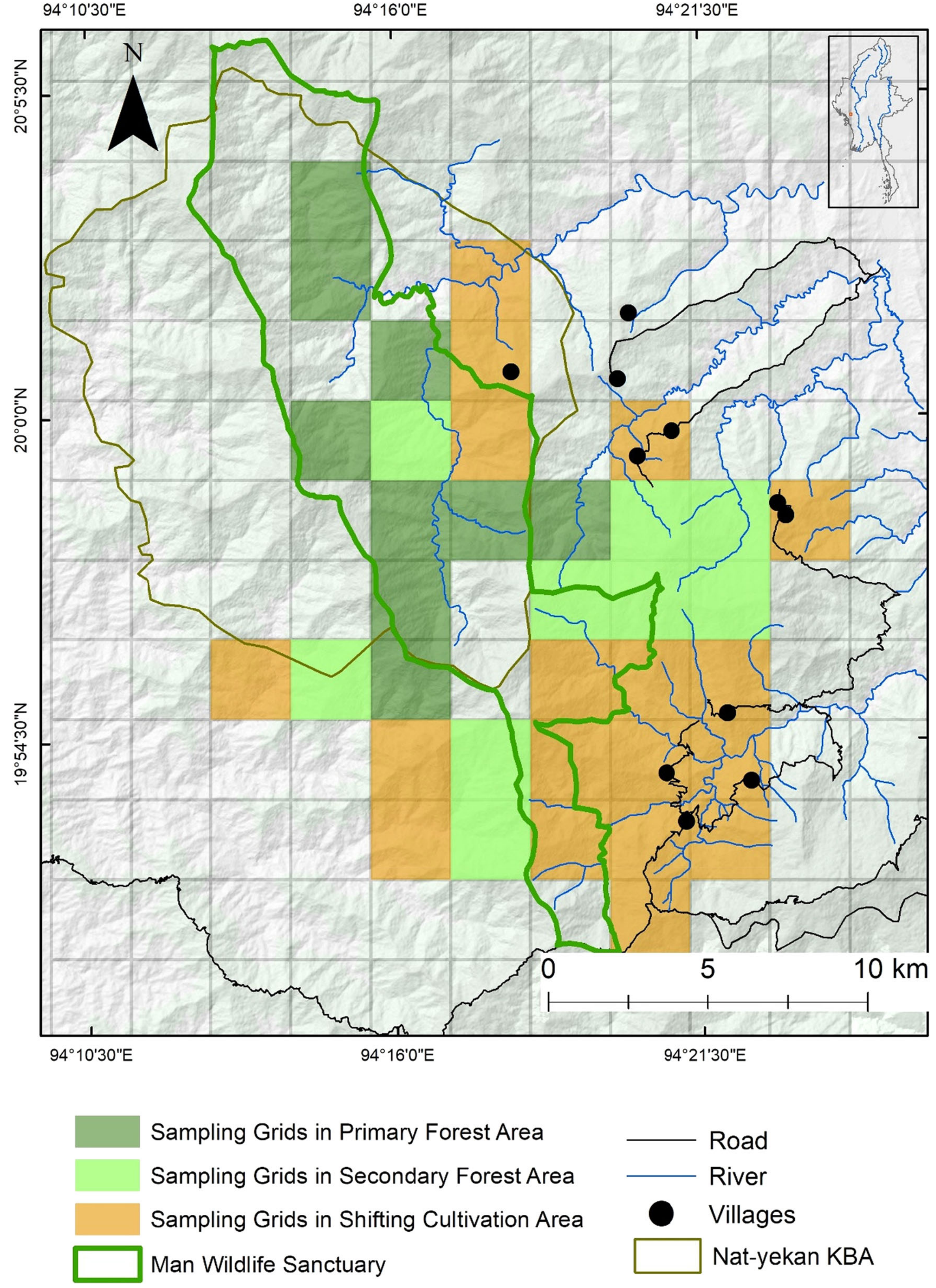

FIGURE 1 | Study area map showing the geographical location of Man Wildlife Sanctuary and its surrounding landscape in the Magway Region, Myanmar.

The human disturbance variables were three fire-related variables: (1) accumulated number of fire points, (2) area of no-pattern fire hotspots, (3) area of sporadic fire hotspots, three deforestation-related variables: (4) number of deforestation points, (5) area of no-pattern deforestation, (6) area of sporadic deforestation hotspots, and the distance from the center of the two listening points to the (7) nearest village and (8) nearest road. Human disturbance variables represent anthropogenic activities such as hunting, logging, and collecting non-timber forest products. In addition, fire occurrence is included as a proxy for human disturbance, as shifting cultivation and uncontrolled fires contribute to habitat degradation. These

TABLE 1 | Covariates collected and calculated within a 1000-m buffer radius around each sampling grid.

Site covariate	Description	Mean (Range)
Landscape		
Elevation (ele)	Mean elevation (m)	871.79 (408.91–1331.96)
Ruggedness (ele.sd)	Standard deviation of elevation (m)	122.54 (74.81–199.99)
Primary forest (pf)	Area of primary forest (km^2)	1.49 (0.23–2.64)
Secondary forest (sf)	Area of secondary forest (km^2)	1.36 (0.48–2.23)
NDVI (ndvi.sd)	Standard deviation of Normalized Difference Vegetation Index (−1 to +1)	0.07 (0.04–0.10)
Canopy heigh (canopy.h)	Mean canopy heigh (m)	13.32 (4.68–21.88)
Canopy cover (canopy.c)	Mean canopy cover (%)	84.07 (60.24–98.36)
Human disturbance		
Deforestation (dforest)	Number of deforestation points	32* (5.00–61.00)
No deforestation pattern detected (d.npd)	Area of no-pattern deforestation hotspots (km^2)	1.19 (0.10–2.93)
Sporadic deforestation Hotspot (d.shs)	Area of sporadic deforestation hotspots (km^2)	0.22 (0.00–1.49)
Fire (fire)	accumulated number of fire points	6* (0.00–33.00)
No fire pattern detected (f. npd)	Area of no-pattern fire hotspots (km^2)	3.02 (2.53–3.14)
Sporadic fire hotspot (f.shs)	Area of sporadic fire hotspots (km^2)	0.08 (0.00–0.61)
Distance to village (d2village)	Nearest distance (km)	4.22 (0.50–12.70)
Distance to road (d2road)	Nearest distance (km)	4.10 (0.03–10.53)
Detection covariate		
Weather (weah)	Observation conditions affecting detection probability	Sunny, cloudy

*Median.

covariates collectively reflect the extent of human impact on the habitat and its potential influence on gibbon abundance. Deforestation data were downloaded from Global Forest Change (Global Forest Change (storage.googleapis.com), while fire data were obtained from NASA's Earth Data Fire Information for Resource Management System (FIRMS) (https://earthdata.nasa.gov/firms). Distances to villages and roads were calculated using the "Near" tool in ArcGIS 10.8.

Landscape and disturbance-related covariates were selected based on their ecological relevance to gibbon habitat use and distribution. Elevation, ruggedness, and NDVI reflect topographic and vegetation variability. Canopy height and cover indicate forest structure critical for arboreal movement. Primary and secondary forests represent habitat types with varying suitability. Deforestation and fire variables assess human-induced disturbance, particularly in shifting cultivation areas. Distances to roads and villages were included as proxies for human pressure, while weather was modeled as a detection covariate due to its influence on gibbon calling behavior.

2.4 | Data Analysis

2.4.1 | N-Mixture Modeling of Gibbon Abundance

We applied an N-mixture model to estimate gibbon group abundance from four replicate counts conducted over four consecutive survey days at each listening point (Royle 2004). This hierarchical method accounts for imperfect detection by incorporating repeated counts, thereby improving the accuracy and reliability of abundance estimates. N-mixture models allow the investigation of relationships between environmental variables and estimated abundance (λ) while incorporating detection probability (p) (Royle 2004; Joseph et al. 2009; Fiske and Chandler 2011). Analyses were conducted using the *pcount* function in the R package "unmarked" (Kellner et al. 2023; R Core Team 2023).

Before analysis, we evaluated outliers and correlations among variables. All variables were standardized by subtracting the mean and dividing by the standard deviation (z-score). Variance Inflation Factor (VIF) values were calculated to assess multicollinearity in each model, with a cut-off of $VIF = 5$ (Zuur et al. 2010; Table S1). Because parameter estimation can be biased by the K-value (the maximum unobserved abundance per site), we tested different K-values (100, 200, and 300) to assess the bias (Kéry and Royle 2016), comparing estimates using Akaike's Information Criterion (Akaike 1973).

We employed a two-step modeling approach to evaluate the variables influencing detection probability and abundance. First, we compared two global models—one with a constant detection probability ($\lambda \sim$ global, $p \sim 1$) and one including weather ($\lambda \sim$ global, $p \sim$ weather)—to assess the impact of weather conditions on detection probability. The global model was considered the most suitable candidate for evaluating overdispersion and was tested for goodness of fit using the Pearson chi-square test (Supporting Information S1: Table S2). The most effective detection covariate was retained for subsequent models exploring ecologically plausible combinations of landscape and human-related disturbance variables to generate the abundance models.

Model comparisons were conducted using AIC, retaining a set of candidate models with $\Delta\text{AIC} \leq 6$ (Burnham and Anderson 2002; Richards 2008). Goodness-of-fit for the best model was evaluated using the Pearson χ^2 P-value in the package "AICcmodavg" with 1000 simulations (Mazerolle 2023). Model averaging was used to estimate the average regression coefficients for covariates in the models, utilizing the "MuMIn" package (Bartoń 2024), with predictors considered influential if their 85% confidence intervals did not overlap zero. This interval aligns model selection and parameter-evaluation criteria more effectively than narrower interval widths (Arnold 2010).

We estimated the mean gibbon density (groups/km^2) across the study area by dividing the total abundance by the effective survey area (36 sampling grids * 3.14 km^2) (Chandler et al. 2011; Dawrueng et al. 2017). The total gibbon abundance across the 36 sampling grids was obtained by summing the site-specific abundance estimates, using the average prediction via the *modavgPred* function to predict the total number of groups within the surveyed area. Confidence intervals (95% CI) for density and abundance were derived from model-averaged predictions to account for uncertainty.

2.4.2 | GLM Analysis of Fire Intensity and Human Disturbance

We also investigated fire intensity and its relationship with human-dominated areas to assess how human activities influence fire occurrence in the study area. To examine the indirect relationship between fire occurrence and human disturbance (distance to villages and roads), we applied a generalized linear model (GLM) with a negative binomial distribution. The negative binomial model was chosen to account for the observed overdispersion in the data. Before analyzing the data, we identified outliers by using scatter plots of response and predictor variables and visualized them using dot plots. We also explored the correlation among all predictor variables by using VIF tests. We validated model assumptions—including overdispersion, zero-inflation, and residual independence—using residual plots and diagnostic tests in the "DHARMa" package (Hartig 2022). We compared all the models using the Akaike Information Criteria with a correction for small sample size (AICc), with the best model identified as that with the lowest AICc and the highest model weight (AICc_{wi}) (Akaike 1973; Burnham and Anderson 2002). All statistical analyses were conducted in R (R Core Team 2023).

3 | Results

3.1 | Gibbon Abundance and Detectability

Model-averaged predictions estimated 181 gibbon groups (95% CI: 141–221 groups) across the 36 sampling grids. The effective survey area covered 113 km^2 (3.14 km^2 * 36 grids), resulting in an estimated density of 1.60 groups/km^2 (95% CI: 1.25–1.96 groups/km^2). Detection probability was strongly influenced by weather conditions. On sunny days, detection probability was high ($p = 0.89$; $\beta = 2.11$, 85% CI: 1.61–2.60), whereas on cloudy days detection probability dropped substantially ($p = 0.24$; $\beta = -1.13$, 85% CI: −1.61 to −0.65).

3.2 | *Landscape* Predictors of Gibbon Abundance

Gibbon abundance showed positive associations with primary forest (pf), canopy cover (canopy.c), canopy height (canopy.h), and areas without detectable fire patterns (f.npd). In contrast, secondary forest (sf) was negatively associated with abundance (Tables 2 and 3). In addition, sporadic fire hot spots (f.shs) and areas with lower fire occurrence displayed marginal negative associations, with confidence intervals narrowly overlapping zero. Elevation (ele) and distance to the villages (d2village) were identified as marginally positive predictors, showing that the higher elevations and locations farther from villages supported greater gibbon abundance.

3.3 | Effects of Fire Disturbance on Gibbon Abundance

We evaluated the relationship between fire intensity (cumulative fire points recorded over 23 years) and human disturbance. Distance to roads emerged as the strongest predictor among candidate models, with the lowest AICc score and 70% model weight support (Table 4). Fire intensity was higher in areas closer to roads than in areas farther away ($\beta = -0.66$, 95% CI: −1.00 to −0.32; Figure 2). The second-ranked model included both distance to villages and distance to roads but received less support due to additional parameters.

4 | Discussion

4.1 | Habitat Quality and Drivers of Gibbon Density

We found that gibbon density varied across habitat types, with higher densities recorded in primary forests and areas with greater canopy cover and height, while lower densities were observed in secondary forests, fire-disturbed areas, and locations closer to human settlements. We observed that gibbon density was positively associated with primary forest areas with excellent canopy cover and canopy height, less fire disturbance, and areas away from human settlements. Consequently, this explains the low density estimated in secondary forests, closer to human settlements and degraded by fire. In contrast, secondary forests, areas affected by fire, and locations closer to human settlements showed a negative association with gibbon density, reflecting the detrimental impact of habitat degradation. Long-term human disturbances, particularly those linked to shifting cultivation, likely reduce food availability and constrain home range size. Shifting cultivation—which is prevalent in the peripheral and lower-elevation zones of the study area and involves land clearing, burning, and short-term cropping

TABLE 2 | Model selection results for factors influencing gibbon abundance using N-mixture models.

Models	K	AIC	ΔAIC	AIC$_{wt}$
λ(pf), p(weah)	4	487.74	0.00	0.097
λ(pf + f.shs), p(weah)	5	488.39	0.65	0.070
λ(fire + d2villlage + ele), p(weah)	6	488.66	0.93	0.061
λ(pf + d2village), p(weah)	5	488.78	1.04	0.058
λ(sf), p(weah)	4	488.79	1.05	0.058
λ(pf + fire), p(weah)	5	489.15	1.41	0.048
λ(f.shs), p(weah)	4	489.15	1.42	0.048
λ(f.npd), p(weah)	4	489.40	1.67	0.042
λ(fire), p(weah)	4	489.46	1.72	0.041
λ(pf + ele + f.shs), p(weah)	6	489.52	1.78	0.040
λ(fire + ele), p(weah)	5	489.58	1.84	0.039
λ(pf + d2village + ele), p(weah)	6	489.67	1.93	0.037
λ(d2village), p(weah)	4	489.74	2.00	0.036
λ(fire + d2village), p(weah)	5	489.76	2.02	0.035
λ(pf + f.shs + d2village), p(weah)	6	489.92	2.18	0.033
λ(pf + ele + f.shs + d2village), p(weah)	7	489.93	2.19	0.033
λ(canopy.h), p(weah)	4	490.28	2.54	0.027
λ(pf + fire + d2village), p(weah)	6	490.41	2.68	0.026
λ(pf + fire + ele), p(weah)	6	490.58	2.84	0.024
λ(pf + fire + d2village + ele), p(weah)	7	490.64	2.91	0.023
λ(d2road), p(weah)	4	490.98	3.24	0.019
λ(pf + fire + d2road), p(weah)	6	491.09	3.35	0.018
λ(fire + d2village + d2road), p(weah)	6	491.61	3.87	0.014
λ(canopy.c), p(weah)	4	491.65	3.92	0.014
λ(.), p(weah)	3	492.16	4.42	0.011
λ(pf + fire + d2village + d2road), p(weah)	7	492.20	4.46	0.010
λ(ele), p(weah)	4	492.90	5.17	0.007
λ(d.npd), p(weah)	4	493.04	5.30	0.007
λ(dforest), p(weah)	4	493.22	5.48	0.006
λ(ndvi.sd), p(weah)	4	493.56	5.83	0.005
λ(ele.sd + pf + d2village + fire + ndvi.sd + d.npd + d.shs + f.shs), p(weah)	11	493.92	6.18	0.004
λ(ele.sd), p(weah)	4	493.96	6.22	0.004
λ(d.shs), p(weah)	4	494.14	6.40	0.004
λ(.), p(.)	2	533.91	46.18	0.000

Note: K = number of parameters; AIC = Akaike Information Criterion; ΔAIC = difference in AIC from the top-performing model; AICwt = Akaike weight (model probability); ele = elevation; ele.sd = ruggedness; pf = primary forest; sf = secondary forest; ndvi.sd = NDVI variability; canopy.h = canopy height; canopy.c = canopy cover; dforest = deforestation; d.npd = no deforestation pattern detected; d.shs = sporadic deforestation hotspot; fire = fire presence; f.npd = no fire pattern detected; f.shs = sporadic fire hotspot; d2village = distance to village; d2road = distance to road; weah = weather.

cycles—creates a mosaic of degraded forest with reduced maturity, simplified canopy structure, and fewer fruiting trees, all of which negatively affect gibbon populations.

The estimated density of *Hoolock hoolock* in Man Wildlife Sanctuary (1.60 groups/km^2) falls within the average range reported across the species' distribution. Lower densities have been estimated in disturbed areas, such as Inani Reserve Forest in southwest Bangladesh, where densities dropped as low as 0.05 groups/km^2 (Naher et al. 2021). Our estimate is similar to Lawachara National Park in Bangladesh (1.69 groups/km^2), a small but well-protected and food-rich forest fragment where gibbons are thought to have compressed their home ranges in response to habitat loss (Hasan et al. 2025).

Differences in gibbon density across sites are likely shaped by habitat quality, forest cover, and levels of human disturbance. Comparable trends have been documented for the Eastern

TABLE 3 | Model-averaged coefficient estimates for predictors of gibbon abundance.

Variables	Estimate	*SE*	85% CI	
			Lower	Upper
Abundance				
Intercept	1.62	0.10	1.472	1.763
pf	0.17	0.12	0.002	0.333
sf	−0.19	0.08	−0.315	−0.072
f.shs	−0.17	0.13	−0.359	0.012
f.npd	0.20	0.10	0.061	0.338
Fire	−0.15	0.12	−0.324	0.027
d2village	0.12	0.10	−0.017	0.266
ele	0.11	0.09	−0.020	0.248
canopy.h	0.16	0.08	0.042	0.277
d2road	0.07	0.13	−0.122	0.253
canopy.c	0.13	0.08	0.010	0.252
d.npd	−0.09	0.09	−0.209	0.037
dforest	−0.08	0.08	−0.193	0.038
ndvi.sd	−0.06	0.08	−0.181	0.055
ele.sd	−0.04	0.08	−0.157	0.083
d.shs	0.01	0.08	−0.101	0.125
Detection probability				
intercept	−1.13	0.33	−1.611	−0.650
Weather (sunny)	2.11	0.35	1.609	2.604

Note: Estimates are derived from model averaging across models with $\Delta AIC \leq 6$. Covariates whose 85% confidence intervals (CI) do not overlap zero are considered to have a strong influence. SE = standard error; CI = confidence interval; pf = primary forest; sf = secondary forest; f.shs = sporadic fire hotspot; f.npd = no fire pattern detected; fire = fire presence; d2village = distance to village; ele = elevation; canopy.h = canopy height; d2road = distance to road; canopy.c = canopy cover; d.npd = no deforestation pattern detected; dforest = deforestation; ndvi.sd = NDVI variability; ele.sd = ruggedness; d.shs = sporadic deforestation hotspot.

TABLE 4 | Model selection results for predicting number of fire occurrence and human disturbance variables—distance to villages (d2village) and distance to roads (d2road)—and the environmental covariate Normalized Difference Vegetation Index (NDVI). Reported are the number of model parameters (K), the Akaike Information Criterion corrected for small sample sizes (AICc), the difference in AICc from the best-supported model (ΔAICc), and Akaike weight ($AICc_{wt}$).

Model	K	AICc	ΔAICc	$AICc_{wt}$
d2road	3	192.67	0.00	0.70
d2village + d2road	4	195.01	2.34	0.22
d2village + d2road + ndvi. sd	5	197.75	5.08	0.06
d2village	3	200.13	7.46	0.02
Intercept-only	2	202.60	9.93	0.01

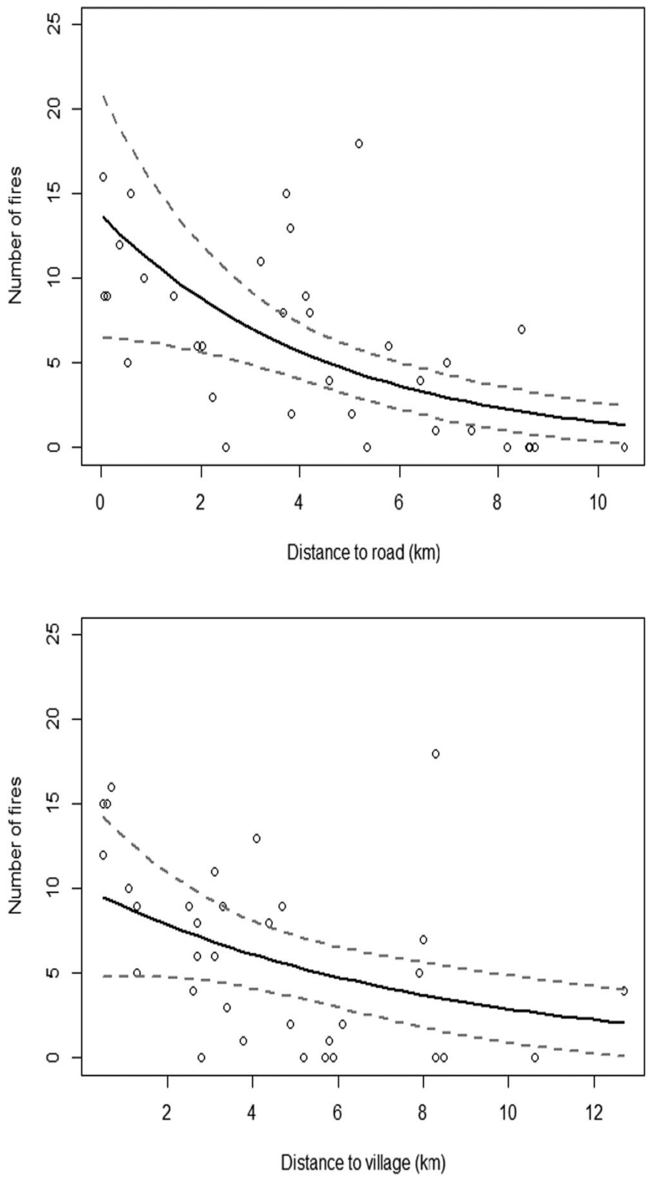

FIGURE 2 | Relationships between fire intensity and human disturbance variables. (a) Relationship with distance to roads, based on the top-ranked model (upper panel). (b) Relationship with distance to villages, based on the second-ranked model (lower panel).

hoolock gibbon (*Hoolock leuconedys*). For example, higher densities have been estimated in well-protected areas such as Hukawng Tiger Reserve (2.81 groups/km^2) and Htamanthi Wildlife Sanctuary (3.13 groups/km^2) in northern Myanmar (Htun et al. 2006). In contrast, lower densities were estimated for Mahamyaing Wildlife Sanctuary (0.97 groups/km^2; Tun et al. 2023) and Indawgyi Biosphere Reserve (0.71 groups/km^2; Lwin et al. 2022), both areas subject to frequent disturbance. These comparisons suggest that conservation status and habitat conditions strongly influence gibbon population density. According to Brockelman and Srikosamatara (1993), Gibbon populations with fewer than two groups per km^2 are considered low density. With a recorded density of 1.60 groups/km^2, the *Hoolock hoolock* population in Man Wildlife Sanctuary falls below this threshold. The comparatively low density recorded at Man Wildlife Sanctuary could result from high levels of human disturbance and poor habitat quality caused by shifting cultivation and agricultural expansion (Geissmann 2013).

4.2 | Effects of Fire and Human Disturbance

The N-mixture model showed that gibbon abundance was significantly influenced by fire disturbances and proximity to human settlements, both closely associated with shifting cultivation. Fire disturbances linked to slash-and-burn agriculture negatively affected gibbon abundance. Human encroachment into the forest areas within gibbon home ranges may increase disturbance, degrade habitat quality, and reduce population densities (Fan and Ai 2011). This finding aligns with previous studies that have shown that fire-induced habitat degradation can disrupt gibbon foraging habitats and lower food availability. For example, fire reduced the density of *Hylobates albibarbis* in the National Laboratory of Peat Swamp Forest, Gunung Palung National Park (Central Kalimantan), by decreasing habitat availability and forcing home range shifts (Cheyne et al. 2019). Similarly, fire-related habitat disturbance has led to a decline in Siamang (*Symphalangus syndactylus*) populations in Bukit Barisan Selatan National Park, Indonesia, through the loss of food resources and strangling fig trees (*Ficus* spp.) (O'Brien et al. 2003). In the Nam Kading National Protected Area in central Laos, white-cheeked gibbon (*Nomascus leucogenys*) groups were less abundant near roads and human settlements due to increased hunting pressure and habitat disturbance (Syxaiyakhamthor et al. 2020), a pattern also observed at Man Wildlife Sanctuary. In the Indawgyi Biosphere Reserve and Mahamyaing Wildlife Sanctuary in Myanmar, *Hoolock leuconedys* densities were found to be higher in areas farther from villages and in regions with lower logging pressure (Lwin et al. 2022; Tun et al. 2023).

Our findings indicate that fire occurrence was significantly higher near roads and human settlements, suggesting that increased human access and activity are key drivers of fire risk. The elevated fire frequency observed near roads and settlements reflects the role of land clearing, shifting cultivation, and infrastructure development in altering fire regimes. Road expansion in particular facilitates access to forested areas, thereby increasing human-induced fire risks (Narayanaraj and Wimberly 2012). At a distance of less than 4 km from roads and human settlements, fire frequency was higher than average in our study area (Figure 2). Roads provide easier access for logging and settlement, which can lead to forest degradation and an increased risk of fire ignition (Narayanaraj and Wimberly 2012). Slash-and-burn agriculture, commonly practiced by local communities, contributes substantially to this increased fire risk in forested landscapes (Padalia and Mondal 2014). Beyond fire, shifting cultivation alters habitat composition, expands human activity into previously undisturbed areas (Geist and Lambin 2002), and compounds threats such as hunting, resource extraction, and land-use conversion (Van Vliet et al. 2012). Together, these pressures intensify the vulnerability of gibbon populations in fragmented landscapes.

4.3 | Conservation Implications and Management Recommendations

Our study confirms that Man Wildlife Sanctuary and its surrounding forest landscape support a viable Western hoolock gibbon population despite ongoing habitat disturbances. Our findings highlight that protecting continuous, undisturbed canopy cover is critical for sustaining gibbon populations, particularly in landscapes increasingly affected by fire and proximity to human activity. The lower densities recorded in secondary forests and fire-affected areas suggest that habitat degradation caused by land clearing and fragmentation is limiting gibbon populations.

Conservation efforts should therefore prioritize the protection of undisturbed forest patches, particularly those identified as high-density gibbon areas. We recommend implementing community-based fire management programs in shifting cultivation zones to reduce fire frequency and mitigate ecological impacts. Collaborating with local village leaders and community forest user groups, the regional township forest department can establish seasonal fire prevention strategies and promote sustainable land-use practices. Habitat reforestation in fragmented areas should be encouraged to reduce habitat loss while supporting local livelihoods. To improve habitat connectivity between isolated forest patches, NGOs and local conservation stakeholders should identify, protect, and restore degraded forest corridors. Awareness campaigns should target both the general public and also youth in nearby schools, incorporating local language and cultural values to promote long-term stewardship. By combining fire management, habitat restoration, and community engagement, these integrated measures—tailored to the ecological and socio-cultural context of the Man Wildlife Sanctuary and its surrounding landscape—can strengthen conservation outcomes and secure the long-term survival of Western hoolock gibbons.

Author Contributions

Aung Lin: writing – original draft, formal analysis, data curation, conceptualization, investigation, methodology, writing – review and editing. **Dusit Ngoprasert:** writing – review and editing, supervision, conceptualization, formal analysis. **Ngwe Lwin:** writing – review and editing, funding acquisition, methodology, project administration. **Niti Sukumal:** formal analysis, methodology, writing – review and editing. **Tommaso Savini:** supervision, conceptualization, writing – review and editing.

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Ethics Statement

The submitted research complies with the journal's Code of Conduct for authors contributing articles. This study did not involve human subjects, experimentation with animals and/or collection of specimens.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data will be made available on request.

References

Akaike, H. 1973. "Maximum Likelihood Identification of Gaussian Autoregressive Moving Average Models." *Biometrika* 60, no. 2: 255–265. https://doi.org/10.1093/biomet/60.2.255.

Arce-Peña, N. P., V. Arroyo-Rodríguez, P. A. D. Dias, I. Franch-Pardo, and E. Andresen. 2019. "Linking Changes in Landscape Structure to Population Changes of an Endangered Primate." *Landscape Ecology* 34, no. 11: 2687–2701. https://doi.org/10.1007/s10980-019-00921-3.

Arnold, T. W. 2010. "Uninformative Parameters and Model Selection Using Akaike's Information Criterion." *Journal of Wildlife Management* 74, no. 6: 1175–1178. https://doi.org/10.1111/j.1937-2817.2010.tb01236.x.

Arroyo-Rodríguez, V., E. Cochoel-de la Mora, S. Mandujano, C. A. Chapman, R. Reyna-Hurtado, and L. Fahrig. 2013. "Assessing Habitat Fragmentation Effects on Primates: The Importance of Evaluating Questions at the Correct Scale." In *Primates in Fragments: Complexity and Resilience*, edited by L. K. Marsh and C. A. Chapman, 13–28. Springer.

Arroyo-Rodríguez, V., and L. Fahrig. 2014. "Why Is a Landscape Perspective Important in Studies of Primates." *American Journal of Primatology* 76, no. 10: 901–909. https://doi.org/10.1002/ajp.22271.

Bartoń, K. (2024). *MuMIn: Multi-Model Inference* (R package version 1.48.4). https://CRAN.R-project.org/package=MuMIn.

Borah, J. R., J. J. Gilroy, K. L. Evans, and D. P. Edwards. 2022. "The Value of Shifting Cultivation for Biodiversity in Northeast India." *Diversity and Distributions* 28, no. 11: 1979–1992. https://doi.org/10.1111/ddi.13605.

Brockelman, W. Y., and S. Srikosamatara. 1993. "Estimation of Density of Gibbon Groups by Use of Loud Songs." *American Journal of Primatology* 29, no. 2: 93–108. https://doi.org/10.1002/ajp.1350290204.

Buchhorn, M., B. Smets, L. Bertels, et al. (2020). *Copernicus Global Land Service: Land Cover 100m: Collection 3: Epoch 2019: Globe* [Data set]. Zenodo. https://doi.org/10.5281/zenodo.3518038.

Burnham, K. P., and D. R. Anderson. 2002. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach* (2nd ed. Springer.

Chan, N., S. Takeda, R. Suzuki, and S. Yamamoto. 2016. "Assessment of Biomass Recovery and Soil Carbon Storage of Fallow Forests After Swidden Cultivation in the Bago Mountains, Myanmar." *New Forests* 47, no. 4: 565–585. https://doi.org/10.1007/s11056-016-9531-y.

Chandler, R. B., J. A. Royle, and D. I. King. 2011. "Inference About Density and Temporary Emigration in Unmarked Populations." *Ecology* 92, no. 7: 1429–1435. https://doi.org/10.1890/10-2433.1.

Cheyne, S. M., B. R. Capilla, A. K., et al. 2019. "Home Range Variation and Site Fidelity of Bornean Southern Gibbons [*Hylobates albibarbis*] From 2010–2018." *PLoS One* 14, no. 6: e0217784. https://doi.org/10.1371/journal.pone.0217784.

Cheyne, S. M., C. J. H. Thompson, A. C. Phillips, R. M. C. Hill, and S. H. Limin. 2008. "Density and Population Estimate of Gibbons (*Hylobates albibarbis*) in the Sabangau Catchment, Central Kalimantan, Indonesia." *Primates* 49, no. 1: 50–56. https://doi.org/10.1007/s10329-007-0063-0.

Chivers, D. J. 2000. "The Swinging Singing Apes: Fighting for Food and Family in Far-East Forests." In *The Apes: Challenges for the 21st Century*, 1–28. Brookfield Zoo.

Critical Ecosystem Partnership Fund. (2012). *Indo-Burma Biodiversity Hotspot: 2012 Update*. https://www.cepf.net/resources?search=indo-burma+2012+update.

Dawrueng, T., D. Ngoprasert, G. A. Gale, S. Browne, and T. Savini. 2017. "Effect of Landscape Variables on the Long-Term Decline of Great Argus in the Rainforest of Southern Thailand." *Bird Conservation International* 27, no. 2: 282–293. https://doi.org/10.1017/S0959270916000277.

Deb, M., S. Choudhury, I. Sharma, et al. 2014. "Nutritional Stress in Western Hoolock Gibbon Due to Adverse Changes in Diet Pattern." *Journal of Microbiology, Biotechnology and Food Sciences* 4, no. 2: 152–156. https://doi.org/10.15414/jmbfs.2014.4.2.152-156.

Fan, P.-F., and H.-S. Ai. 2011. "Conservation Status of the Eastern Hoolock Gibbon (*Hoolock leuconedys*) in China." *Gibbon Journal* 6: 22–25.

Fiske, I., and R. Chandler. 2011. "Unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance." *Journal of Statistical Software* 43, no. 10: 1–23.

Forest Department. (2015). *National Biodiversity Strategy and Action Plan 2015–2020* (p. 137). Ministry of Environmental Conservation and Forestry, Myanmar.

Funk, C., P. Peterson, M. Landsfeld, et al. 2015. "The Climate Hazards Infrared Precipitation With Stations—A New Environmental Record for Monitoring Extremes." *Scientific Data* 2: 150066. https://doi.org/10.1038/sdata.2015.66.

Geissmann, T. (2013). *The Conservation Status of Hoolock Gibbons in Myanmar*. Gibbon Conservation Alliance. https://www.gibbons.de/main/research/publications.html.

Geist, H. J., and E. F. Lambin. 2002. "Proximate Causes and Underlying Driving Forces of Tropical Deforestation." *BioScience* 52, no. 2: 143–150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2.

Hartig, F. (2022). *DHARMa: Residual Diagnostics for Hierarchical (Multi-Level/Mixed) Regression Models* (R package version 0.4.6). R Foundation for Statistical Computing. https://florianhartig.github.io/DHARMa/.

Hasan, S., H. Naher, T. Akhter, et al. 2025. "Impact of Seasonality on Food Selection and Home Range Size of the Western Hoolock Gibbon (*Hoolock hoolock*)." *International Journal of Primatology* 46, no. 1: 69–95.

Htun, S., Z. H. Aung, W. Naing, et al. Forest Department, Nature and Wildlife Conservation Division, & Wildlife Conservation Society–Myanmar Program. (2006). *Final Report on Conservation of the Hoolock Gibbon (Hylobates hoolock) in the Hukaung Tiger Reserve, North Myanmar: Population Surveys, Threat Assessment and Conservation Outreach, September 2006*. Wildlife Conservation Society–Myanmar Program.

Joseph, L. N., C. Elkin, T. G. Martin, and H. P. Possingham. 2009. "Modeling Abundance Using N-Mixture Models: The Importance of Considering Ecological Mechanisms." *Ecological Applications* 19, no. 3: 631–642. https://doi.org/10.1890/07-2107.1.

Kellner, K. F., A. D. Smith, J. A. Royle, M. Kéry, J. L. Belant, and R. B. Chandler. 2023. "The Unmarked R Package: Twelve Years of Advances in Occurrence and Abundance Modelling in Ecology." *Methods in Ecology and Evolution* 14, no. 7: 1408–1415. https://doi.org/10.1111/2041-210X.14123.

Kéry, M., and J. A. Royle. 2016. *Applied Hierarchical Modeling in Ecology: Analysis of Distribution, Abundance and Species Richness in R and BUGS* (1). Academic Press.

Lawrence, D., C. Radel, K. Tully, B. Schmook, and L. Schneider. 2010. “Untangling a Decline in Tropical Forest Resilience: Constraints on the Sustainability of Shifting Cultivation Across the Globe.” *Biotropica* 42, no. 1: 21–30. https://doi.org/10.1111/j.1744-7429.2009.00599.x.

Lwin, N., D. Ngoprasert, N. Sukumal, S. Browne, and T. Savini. 2022. “Status and Distribution of Hoolock Gibbon in the Newly Established Indawgyi Biosphere Reserve: Implication for Protected Area Management.” *Global Ecology and Conservation* 38: e02209. https://doi.org/10.1016/j.gecco.2022.e02209.

Lwin, N., N. Sukumal, and T. Savini. 2021. “Modelling the Conservation Status of the Threatened Hoolock Gibbon (*Genus Hoolock*) Over Its Range.” *Global Ecology and Conservation* 29: e01726. https://doi.org/10.1016/j.gecco.2021.e01726.

Marsh, L. K., C. A. Chapman, and V. Arroyo-Rodríguez. 2003. “Primates in Fragments.” In *Primates in Fragments: Ecology and Conservation*, edited by L. K. Marsh, 6–7. Kluwer Academic/Plenum Publishers.

Marshall, A. J., and M. Leighton. 2006. “How Does Food Availability Limit the Population Density of White-Bearded Gibbons?” In *Feeding Ecology in Apes and Other Primates*, edited by G. Hohmann, M. Robbins, and C. Boesch, 48, 313–341. Cambridge University Press.

Mazerolle, M. J. (2023). *AICcmodavg: Model Selection and Multimodel Inference Based on (Q)AIC(c)* (R Package Version 2.3-4). https://cran.r-project.org/package=AICcmodavg.

Mukul, S. A., and J. Herbohn. 2016. “The Impacts of Shifting Cultivation on Secondary Forest Dynamics in Tropics: A Synthesis of the Key Findings and Spatio-Temporal Distribution of Research.” *Environmental Science & Policy* 55: 167–177. https://doi.org/10.1016/j.envsci.2015.10.005.

Muzaffar, S. B., M. A. Islam, M. M. Feeroz, et al. 2007. “Habitat Characteristics of the Endangered Hoolock Gibbons of Bangladesh: The Role of Plant Species Richness.” *Biotropica* 39, no. 4: 539–545. https://doi.org/10.1111/j.1744-7429.2007.00298.x.

Naher, H., H. Al-Razi, T. Ahmed, S. Hasan, A. Jaradat, and S. B. Muzaffar. 2021. “Estimated Density, Population Size and Distribution of the Endangered Western Hoolock Gibbon (*Hoolock Hoolock*) in Forest Remnants in Bangladesh.” *Diversity* 13, no. 10: 490. https://doi.org/10.3390/d13100490.

Narayanaraj, G., and M. C. Wimberly. 2012. “Influences of Forest Roads on the Spatial Patterns of Human- and Lightning-Caused Wildfire Ignitions.” *Applied Geography* 32, no. 2: 878–888. https://doi.org/10.1016/j.apgeog.2011.09.004.

Nath, T. K., M. Jashimuddin, M. Kamrul Hasan, M. Shahjahan, and J. Pretty. 2016. “The Sustainable Intensification of Agroforestry in Shifting Cultivation Areas of Bangladesh.” *Agroforestry Systems* 90, no. 3: 405–416. https://doi.org/10.1007/s10457-015-9863-1.

O'Brien, T. G., M. F. Kinnaird, A. Nurcahyo, M. Prasetyaningrum, and M. Iqbal. 2003. “Fire, Demography and the Persistence of Siamang (*Symphalangus syndactylus*: Hylobatidae) in a Sumatran Rainforest.” *Animal Conservation* 6, no. 2: 115–121. https://doi.org/10.1017/S1367943003003159.

Padalia, H., and P. P. Mondal. 2014. “Spatio-Temporal Trends of Fire in Slash and Burn Agriculture Landscape: A Case Study From Nagaland, India.” *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* II–8, no. 8: 53–59. https://doi.org/10.5194/isprsannals-II-8-53-2014.

R Core Team. (2023). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.r-project.org/.

Richards, S. A. 2008. “Dealing With Overdispersed Count Data in Applied Ecology.” *Journal of Applied Ecology* 45, no. 1: 218–227. https://doi.org/10.1111/j.1365-2664.2007.01377.x.

Royle, J. A. 2004. “N-Mixture Models for Estimating Population Size From Spatially Replicated Counts.” *Biometrics* 60, no. 1: 108–115. https://doi.org/10.1111/j.0006-341x.2004.00142.x.

Schmid, M., A. Heinimann, and J. G. Zaehringer. 2021. “Patterns of Land System Change in a Southeast Asian Biodiversity Hotspot.” *Applied Geography* 126: 102380. https://doi.org/10.1016/j.apgeog.2020.102380.

Syxaiyakhamthor, K., D. Ngoprasert, N. Asensio, and T. Savini. 2020. “Identifying Priority Areas for the Conservation of the Critically Endangered Northern White-Cheeked Gibbon *Nomascus leucogenys* in Northern Lao.” *Oryx* 54, no. 5: 767–775. https://doi.org/10.1017/S0030605318001515.

Thet, A. P. P., and N. Tokuchi. 2021. “The Influences of Traditional Shifting Cultivation on Soil Properties and Vegetation in the Bago Mountains, Myanmar.” *Human Ecology* 49, no. 5: 655–664. https://doi.org/10.1007/s10745-021-00255-8.

Tolan, J., H.-I. Yang, B. Nosarzewski, et al. 2024. “Very High Resolution Canopy Height Maps From RGB Imagery Using Self-Supervised Vision Transformer and Convolutional Decoder Trained on Aerial LiDAR.” *Remote Sensing of Environment* 300: 113888. https://doi.org/10.1016/j.rse.2023.113888.

Tran, D. V., A. Osawa, and T. T. Nguyen. 2011. “Recovery of Vegetation Structure and Species Diversity After Shifting Cultivation in Northwestern Vietnam, With Special Reference to Commercially Valuable Tree Species.” *International Scholarly Research Notices* 2011: 751472. https://doi.org/10.5402/2011/751472.

Tun, W. K. K. N., N. Sukumal, D. Ngoprasert, N. M. Shwe, and T. Savini. 2023. “Gibbon Population Status and Long-Term Viability: Implication for a Newly Established Protected Area Management.” *Global Ecology and Conservation* 45: e02534. https://doi.org/10.1016/j.gecco.2023.e02534.

Van Vliet, N., O. Mertz, A. Heinimann, et al. 2012. “Trends, Drivers and Impacts of Changes in Swidden Cultivation in Tropical Forest–Agriculture Frontiers: A Global Assessment.” *Global Environmental Change* 22, no. 2: 418–429. https://doi.org/10.1016/j.gloenvcha.2011.10.009.

Wikramanayake, E., E. Dinerstein, C. J. Loucks, et al. 2002. *Terrestrial Ecoregions of the Indo-Pacific: A Conservation Assessment*. Island Press.

Zuur, A. F., E. N. Ieno, and C. S. Elphick. 2010. “A Protocol for Data Exploration to Avoid Common Statistical Problems.” *Methods in Ecology and Evolution* 1: 3–14. https://doi.org/10.1111/J.2041-210x.2009.00001.X.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Supplementary Table S1: VIF scores for covariates used in the global model. **Supplementary Table S2:** Pearson chi-square test results for model fit.