Spatial modelling for predicting potential wildlife distributions and human impacts in the Dja Forest Reserve, Cameroon

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Abstract

Protected areas (PAs) are currently the cornerstones for biodiversity conservation in many regions of the world. Within Africa's moist forest areas, however, numerous PAs are under significant threats from anthropogenic activities. Adequate technical and human resources are required to manage the wildlife within PAs satisfactorily. SMART (Spatial Monitoring And Reporting Tool) software has been developed to aid in fluidly displaying, managing, and reporting on ranger patrol data. These data can be analysed using spatial modelling to inform decision-making. Here we use Favourability Function modelling to generate risk maps from the data gathered on threats (fire, poaching and deforestation) and the presence of Western gorilla (*Gorilla gorilla gorilla*), chimpanzee (*Pan troglodytes*) and African forest elephant (*Loxodonta cyclotis*) in the Dja Forest Reserve (DFR), southern Cameroon. We show that the more favourable areas for the three study species are found within the core of the DFR, particularly for elephant. Favourable areas for fires and deforestation are mostly along the periphery of the reserve, but highly favourable areas for poaching are concentrated in the middle of the reserve, tracking the favourable areas for wildlife. Models such as the ones we use here can provide valuable insights to managers to highlight vulnerable areas within protected areas and guide actions on the ground.

1. Introduction

Protected areas (PAs) aim to conserve nature by minimizing human pressures and threats operating within their boundaries. Although PAs are known to perform better than the broader landscape (Barnes et al., 2016; Gray et al., 2016), numerous studies suggest that biodiversity continues to decline within them (Craigie et al., 2010; Geldmann et al., 2013). Numerous PAs within Africa's moist forest regions, often created to safeguard large charismatic fauna and other natural resources, are under significant threats from anthropogenic activities such as deforestation, fires and hunting (Joppa and

Pfaff, 2011; Nelson and Chomitz, 2011; Tranquilli et al., 2014). The persistence of wildlife in PAs ultimately depends on increasing conservation efforts to combat such threats (Arcese et al., 1995; Jachmann and Billiouw 1997; Bruner et al., 2001; de Merode and Cowlishaw, 2006; de Merode et al., 2007).

Law enforcement in PAs in the Congo Basin is notoriously underfinanced (Wilkie et al., 2001). Thus, tools that enable the often, resource-limited (in technology, weapons and personnel) site-based staff, to better patrol more areas with greater regularity, have been developed recently. These have resulted from the increased accessibility of geospatial technologies associated with Global Positioning Satellites (GPS), remote sensing and Geographic Information Systems (GIS) (O'Neil 2005). Two applications, CyberTracker and SMART (Spatial Monitoring And Reporting Tool), are now available to improve the effectiveness of wildlife law enforcement patrols and site-based conservation activities on the ground. SMART contains a suite of programs that can use mobile data collected with the CyberTracker App (CyberTracker, 2018). CyberTracker operates within a GPS enabled mobile device e.g. smartphone or a Personal Digital Assistant (PDA) to collect observation and GPS data in a single unit. On return from their patrols, data collected by rangers as part of their daily work (e.g. wildlife observations, poaching encounters) can be transferred to directly into the SMART database in a semi-automated process. These tools are open source and non-proprietary and are currently deployed in hundreds of sites around the world. (Henson et al., 2016, SMART, 2017, 2018).

Spatial modelling of observation data gathered using CyberTracker and SMART over a relevant period of time can be used to predict significant areas of threats relative to areas of abundance of the target species across a PA including in unpatrolled areas. Increasing the probability of detecting illegal activities improves the efficacy of PA law enforcement (Leader-Williams and Milner-Gulland, 1993), leading managers to target areas where threats are most likely to occur (Campbell and Hofer, 1995). Mapping and predictions of threat occurrence can be effective in helping law enforcement reduce deforestation threats (Linkie et al., 2010) and can result in cost-efficient prevention of illegal activities (Plumptre et al., 2014).

In this paper, we focus attention on understanding the distribution of and threats affecting the Endangered chimpanzee (*Pan troglodytes*), the Critically Endangered Western lowland gorilla (*Gorilla gorilla gorilla*), and the Endangered African forest elephant (*Loxodonta cyclotis*)[1] within the Dja Forest Reserve (DFR) in southern Cameroon. The DFR is a key stronghold for these flagship species and is one of Africa's most biodiverse rainforests. Despite its importance, the state of conservation of the reserve is precarious, due to the continuing impact of uncontrolled commercial hunting and other illegal activities. As a result, the DFR is likely to be inscribed on the List of World Heritage in Danger (UNESCO, 2018). A number of measures have been proposed to strengthen the institutional and operational framework for management of the DFR, including the strengthening of technical and logistical capacities (UNESCO, 2018).

Adequate law enforcement patrolling within the DFR is restricted by the terrain's inaccessibility and by the small (75-man) ranger force currently in place. Given this situation, timely analyses of data gathered by these patrols can be used to assist the ranger force become more strategic. Here, we utilise patrol data on the distribution of the target species and pressures on these, to generate maps of high-pressure areas for wildlife. These maps are created using Favourability Function (FF) modelling (Real et al., 2006; Acevedo and Real, 2012). FF is a procedure based on logistic regression that removes the effect of species prevalence from presence probabilities, thus evening out model predictions for different species and factors so that they can be directly combined. FF modelling has been used to resolve species conservation issues (e.g. Estrada et al., 2008; Fa et al., 2014). Based on the results of our modelling we discuss possible management and conservations interventions that could be applied to better protect large mammals in protected areas.

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[1] Although there is still some debate over the distinction of the African Forest Elephant, here we follow Wittemyer (2011) and refer to the elephant species in the DFR as *L. cyclotis.*

2. Material and methods

2.1. Study area

The DFR (2°50 – 3°30 N, 12°20 – 13°40 E) in southeastern Cameroon is bounded on three sides by the Dja River (Figure 1), a major tributary of the Congo River. The DFR was designated as a Biosphere Reserve under the UNESCO Man & Biosphere Programme in 1981 and is classified as an IUCN Management Category VI: Managed Resource Protected Area. At the time of the World Heritage listing, 90% of the area was considered intact and human pressure was low.

Our study area comprised the entire DFR and up to 21 km around the limits of the reserve so as to include the tracks followed by ranger patrols (see Supplementary Figure 1). Covering 5,260 km^2 and 600–700 m above sea level, the DFR is one of the largest protected areas of lowland rainforest across tropical Africa. Monthly average temperature in the region is 23.5 - 24.5 °C and annual rainfall 1,180 – 2,350 mm. Vegetation in the DFR lies within a transitional zone between the Atlantic equatorial coastal forests of southern Nigeria and western Cameroon, and the evergreen forests of the north-western Congo lowlands. Atlantic, semi-deciduous, Congolese and monospecific forest types are present within the DFR but tree cover is dominated by dense semievergreen Congo rainforest.

2.2. Patrol data

Operating under the auspices of an agreement between The African Ape Initiative (AAI) of the African Wildlife Foundation (AWF) and the Service de Conservation-DFR (SC-DFR), anti-poaching patrols completed pre-identified routes within the DFR (see routes in Supplementary Figure 2 and 3). While AAIsupported anti-poaching patrol efforts started in Sept. 2013, here we use data for Feb. – Apr. 2015 and Jan. – Mar. 2016. During this period, a total of 15 patrols were deployed, an average of 2.5 patrols per month (range 1 – 4), covering a distance of 230.7 km (range 72 – 458 km) per patrol, and 22.5 days per patrol (range 3 -51 days).

In total, patrols covered 1,384 km over 192 patrol days (Dupain et al., 2017). Each patrol team undertook 10-day missions within pre-determined itineraries; routes were decided on the basis of knowledge of the terrain, but were not randomly chosen. Data were gathered from 6h to 17h during patrol days. Patrols would seize hunting gear and fraudulently collected products, would destroy traps and camps, collect cartridges and other polluting objects, and be involved in sensitization and eviction of offenders. Tracklogs, photos and observations of mammals and human activities were georeferenced and recorded. For this paper, we used only data of elephant dung, gorilla nests, chimpanzee nests and encounters with hunting camps, poachers, cartridges and snares.

All patrols (each composed of six guards, and four local village porters) carried a PDA equipped with CyberTracker for download to a computer running SMART. A total of 60 out of 75 eco-guards were trained in the use of the PDA and to operate Cyber-Tracker and SMART; all data collection protocols were approved by the Conservation Department in Cameroon.

2.3. Modelling variables

Patrol observations data of the presence of the three species were used to delimit the distribution of wildlife within the DFR. Threat data based on poaching signs, forest loss and fires, the latter two derived from remote sensing, were dependent variables in our models. Independent variables included spatial data on environmental and anthropogenic factors obtained from non-field based sources. Records for each variable were assigned to 0.5×0.5-km grid squares covering the entire study area.

Dependent variables

We used presence records of chimpanzees, gorillas and elephants gathered by DFR park personnel during 2015 and 2016. Park personnel employed CyberTracker hand-held devices, allowing them to record observations quickly and easily prior to upload into the fully compatible SMART software. For each positive contact (Supplementary Figure 1), we fixed a 2.5 km buffer zone for gorillas and chimpanzees, and 5.0 km for elephants. The size of these buffer zones was based on the average daily distances travelled by each species in Wilson and Mittermeier (2011) and Mittermeier et al. (2013). For modelling purposes, we assumed that the species was present in all the 0.5×0.5-km squares included within these buffers.

Data on poaching consisted of geo-referenced records of traps and ammunition cartridges found by the DFR staff during their patrols. We assumed that poachers were active within a maximum of a 10-km radius buffer around each record from data on the area covered by trappers in Equatorial Guinea (Kümpel, 2006).

Forest loss within 0.5×0.5-km squares was derived from comparisons of newly deforested areas between 2001 and 2014 (i.e. a 15-year period prior to our wildlife evaluation) available from Hansen (2013) and from the Global Forest Change web site (https://earthenginepartners.appspot.com/science2013-global-forest). Fire presence was defined as all 0.5×0.5-km squares containing active fire observations between 2001 and 2014 in NASA's FIRMS database (https://firms.modaps.eosdis.nasa.gov) (Supplementary Figure 2).

Absences for all variables based on field personnel observations (i.e. wildlife and poaching) were defined as all non-presence in 0.5×0.5-km squares within a buffer area around the tracks followed by ranger patrols (Supplementary Figure 1 and Supplementary Figure 2a). This minimized bias caused by uneven sampling throughout the study area since models are initially developed within the regions of the study area that were sampled by ranger patrols. Buffer width was specific to every variable, according to the above. Using this criterion, there were 2,388 presences and 7,994 absences for gorillas, 2,630 presences and 7,752 absences for chimpanzees, 8,542 presences and 6,503 absences for elephants as well as 20,858 presences and 3,047 absences for poaching. For forest loss and fire, all non-presence 0.5×0.5km squares within the study area were considered as absences, given the unbiased nature of remote sensing observations.

Independent variables

Predictors on which the models were based, consisted of 39 variables which described climate, topography, soils, land use and anthropogenic descriptors (Supplementary Table 1). Variable values per 0.5×0.5-km square were calculated using the ZONAL tool of the ArcMap v.10.1 (ESRI©2012) software, starting from 100-m^2 resolution raster layers. We computed average values for each predictor except for the land-use variables, for which squarearea proportions covered by each use were considered.

In order to consider autocorrelation resulting from the purely spatial structure of species distributions (Sokal and Oden, 1978), we designed a purely spatial independent variable following the 'trend surface approach' (Legendre and Legendre, 1998). To this end, different combinations of average latitude (Y) and longitude (X) were defined (i.e. X, Y, XY, X^2, Y^2, X^2Y, XY^2, X^3, Y^3), and a backward-stepwise logistic regression of presences/absences was run on these combinations. This modelling method commences with the full combinations of latitude and longitude and then iteratively removes the least significant predictor variable. Because it is based on the location of presences, and not on variables that describe possible causes of distribution, this model is more predictive than explanatory. For that reason, we use backward steps which generates a more conservative model with respect to the number of variables that remain in the model. Then we used the logit of this regression as the spatial independent variable.

2.4. Predictive models

Model fitting and evaluation

Models defining the distribution of environmentally favourable areas for each species and threat were developed using the Favourability Function (FF), as described by Real et al. (2006) and Acevedo and Real (2012):

$$F = (((P)/(1-P))/((n_1/n_0)+(P/(1-P))))$$

where F is environmental favourability (0-1), *P* is the presence probability, and n_1 and n_0 are the numbers of presences and absences, respectively. *P* was calculated using forward-backward stepwise logistic regression, according to the independent variables shown in Supplementary Table 1 and the spatial variables. We have preferred steps forward, against backward steps, to minimize the number of variables in the model, thus favouring its explanatory capacity with respect to the causes of the distribution.

Type I errors, potentially caused by the large number of variables employed in the process, were controlled by using Benjamini and Hochberg's (1995) False Discovery Rate (FDR).

To minimise multicollinearity, we applied a three-step procedure. First, we avoided using variables that had correlation values (Spearman R) greater than 0.8, by removing the least significant within each pair of highly correlated variables. From these, we accepted only significant variables with a FDR of $q < 0.05$. Finally, forward-backward stepwise logistic regression will not consider correlated variables in the final model. Variables enter the equation by forward selection, so that the first variable explains the highest proportion of the variation observed, the second variable explains the highest proportion of the residual variation (i.e. variation not explained by the first variable), and so on. For this reason, the final model does not usually include correlated variables, and if two correlated variables enter it is because one explains part of the variation not explained by the other.

The classification capacity of the models obtained was evaluated using four indices: sensitivity (proportion of correctly classified presences), specificity (proportion of correctly classified absences), correct classification rate (CCR: proportion of presences and absences correctly classified) and Cohen's Kappa (proportion of specific agreement; Fielding and Bell, 1997). We used the area under the receiver operating characteristic curve (AUC) to assess the discrimination capacity of the models (Lobo et al., 2008). The significance of every independent variable in the model was assessed using the Wald test.

Model extrapolation

Wildlife and threat of poaching models, fitted in training areas constrained to buffers around ranger patrol tracks, were extrapolated to the whole of the study area using the following equation (Real et al., 2006):

$$F = e^y/[(n_1/n_0) + e^y]$$

where n_1 and n_0 are presence and absence numbers within the training area, e is the base of the natural logarithms, and y is the linear combination of predictor variables (i.e. the logit) of the logistic regression defining P (see above).

Model extrapolations were made only to the 0.5×0.5-km squares whose variable values were within the dominion of the Favourability Function, i.e. were in the range of values shown by the model variables within the training area. We only accepted a 10% tolerance above and below. This precaution avoided projections to zones that were not environmentally represented in the area used for model training.

2.5. Wildlife and risk maps

In this paper we define threat as an action (poaching, fire, forest loss) likely to cause damage, harm or loss. We define risk as the potential or possibility of an adverse consequence resulting from the combined effects of one or more threats.

Using the average of favourability models obtained for the three target species we calculated a "Wildlife Index (WI)". A “Threat Index (TI)” was derived from the average of the three threat models. We employed the average rather than the sum so as to maintain the range of resulting values between 0 and 1. We combined the threat and wildlife indices to derive an overall map (which we call a risk map) to show where wildlife was more likely to be affected by threats either separately or combined. We divided the study area by the following favourability values for each index: High (H): index values ≥0.8. IntermediateHigh (IH): indices values between 0.5 and 0.8. Intermediate-Low (IL): indices values between 0.5 and 0.2. Low (L): indices values ≤ 0.2.

3. Results

3.1. Wildlife models

We obtained significant favourability models for all three species (Table 1, Figure 2). These models had acceptable values of discrimination capacity (AUC >0.745), and fair classification capacity values (Cohen's Kappa value >0.300) as shown in Table 2. All showed a fairly high proportion of correctly classified presences and absences; values being ≥0.635 for sensitivity and specificity. The correct classification rate was always ≥0.670.

Table 1 and 2 around here

Greater distances to the nearest road were associated with higher favourability for the presence of all species, but larger distances from towns and villages were also significantly related to more favourable areas for gorillas. Maps showed that highly favourable areas within the core of the DFR were typical for all three species. Highly favourable areas for gorillas and elephants were also found along the northern part of the DFR (Figure 2a, 2c), but not for chimpanzees (Figure 2b). The latter species had highly favourable areas along the south-eastern area of the park as well as in the central region. Overall, larger highly favourable areas within the centre of the DFR were more typical for elephants (Figure 2c) than for the other two species. For all three species combined, more favourable areas were within the interior of the DFR (Figure 2d), with less favourable areas along a ring from the west to the east of the park.

3.2. Threat models

Significant favourability models were also obtained for the three threat variables considered in this study (Table 3). Discrimination capacity was acceptable (AUC >0.749; Table 2) but classification capacity was low for fire (Kappa = 0.088), moderate for poaching (Kappa = 0.422) and fair for deforestation (Kappa = 0.269). The three models showed a fairly high proportion of correctly classified presences and absences (sensitivity and specificity values were always ≥0.685).

Table 3 around here

Proximity to roads and to towns and villages were significantly related to high favourability values for forest loss and fire; proximity to agriculture was also relevant. However, environmental variables defining high favourability for poaching were a combination of climatic variables (mainly high precipitation in the wettest month and low precipitation in the warmest quarter), topohydrography (greater distance from navigable streams) and soil (low sand percentage). Favourable areas for poaching were largely concentrated around the centre of the reserve (Figure 2e), but favourable areas for forest loss and fires were found outside the DFR (Figure 2f, 2g). The combined TI (Figure 2h) indicated that areas that were most favourable for all threats were along the western boundary and to a lesser extent just outside the eastern border of the DFR.

3.3. Combining wildlife and threat models

TI-WI maps for each threat factor indicated that the more favourable areas for poaching actually overlapped considerably with the more favourable areas for wildlife, in fact occupying most of the DFR (Figure 3a). In contrast, the highest risk from forest loss and fires were concentrated along the western region of the study area, but always outside the DFR (Figure 3b, 3c).

The combined TI-WI map showed that the highest levels of risk for wildlife were found along the western and the northern sectors of the DFR (Figure 3d). Along the east of the DFR, high-risk areas are found just outside the park.

4. Discussion

Electronic monitoring tools such as SMART and CyberTracker have been instrumental in empowering protected area managers to record and assess the state of faunal or other elements under their care. Nonetheless, the use of these tools is only effective if the plethora of law enforcement monitoring data that they are able to generate can be analysed promptly to guide management on the ground. Both SMART and CyberTracker, which are free and open-source, are highly configurable and therefore widely accessible to the conservation community, which often has widespread data-management needs. Although SMART is a relatively new piece of software that will no doubt develop further, the conservation community would benefit from parallel initiatives for development of analyses that integrate patrol data with independent data sources to inform more effective targeting of limited management assets. Together, CyberTracker and SMART provide an integrated and accessible platform for systematic collection and aggregation of structured, actionable wildlife and threat distribution data from protected area patrols and monitoring programmes. Spatial modelling can add value to these data enabling managers to better understand events occurring within the protected areas and facilitate decision-making, whether in response to issues arising or in measuring the impact of new initiatives. Examples of the use of ranger patrol data alongside spatial modelling are still relatively scarce (but see Critchlow's et al. 2015 use of Bayesian methods to improve ranger patrols within protected areas).

Species distribution models (SDMs) are widely used in the fields of macroecology, biogeography and biodiversity research for modelling species geographic distributions based on correlations between known occurrence records and the environmental conditions at occurrence localities (Elith and Leathwick, 2009). Although a number of SDMs such as Ecological Niche Factor Analysis (ENFA), Maximum Entropy Approach (MaxEnt) and FF (Hirzel et al., 2002; Phillips et al., 2006; Real et al., 2006; Elith and Leathwick, 2009) are commonly used, only favourability values for different modeled units (in our case study species and threats) can be compared in absolute terms.

Favourability provides commensurate values and is independent from presence prevalence (Acevedo and Real, 2012). Such characteristics are particularly useful in conservation biology such as in defining areas where a group of species may be more vulnerable to different factors (Fa et al., 2014) or when models for a large number of species need to be combined to define relevant areas for conservation (Estrada-Peña et al., 2008). In this paper, we apply FF modelling which is an approach that has advantages over other more widely used spatial methods (see Olivero et al., 2016; Acevedo and Real, 2012). FF like logistic regression relies on assumptions such as the independence of observations, and limited multicollinearty which are not always restricted met. We show how ranger and satellite data can be effectively overlaid to model the distribution of animal species of conservation interest, to determine areas likely to be more at risk from poaching and other anthropogenic factors.

Scarce technical and human resources and inadequate resource management are among the main reasons for the decline in wild populations of many threatened large mammal species across the Congo Basin, both inside and outside protected areas (Campbell et al., 2008; Kühl et al., 2017). Because of this, the more effective application of existing resources could benefit from the use of suitable tools for wildlife management and conservation. In this study, we propose a conservation biogeography approach to assist in the protection of wild populations of three threatened, iconic African mammal species. Our models clearly suggest that the most favourable areas for gorillas, chimpanzees and elephants are found within the core of the studied protected area, the DFR. According to this, isolation is a highly relevant factor, since the most important variable explaining the presence of the three species in our wildlife models was "distance to roads". This also explains why large areas located within the core of the DFR, at least during our study period, are highly favourable for the three species (Figure 4). These results are corroborated by field work undertaken by one of our authors, (JD) who undertook a transect of 98 km through the middle of the DFR, and who found higher levels of wildlife signs, particularly of elephants, within the core of the reserve (Dupain et al., 2017). Our models clearly suggest that favourable areas for poaching, as expected, correspond with the more favourable areas for wildlife. In both cases, areas that are more distant from roads, from navigable rivers and from human settlements, hence more remote, were more favourable to poaching and wildlife. Also, these areas, primarily along the north-western region of the reserve, are those with a higher proportion of soil. This may point to the fact that more sandy soils are linked to poorer forests, in terms of plant and animal diversity, so naturally poachers are likely to search for animals to hunt in remote forests in deeper soils.

Our results confirm the findings of regional analyses of the spatial relationship between the distribution of gorillas, chimpanzees and elephants and human activities in other parts of the Congo Basin (Stokes et al., 2010; Maisels et al., 2013; Strindberg et al., 2018). In the case of the great apes, Strindberg et al. (2018) showed that human-related variables (in particular distance to roads and human population densities) as well as canopy height and Ebola (natural variables) were important predictors of great ape density and distribution. Stokes et al. (2010) also indicated that chimpanzees show a clear preference for unlogged or more mature forests and human disturbance had a negative influence on chimpanzee abundance, in spite of anti-poaching interventions. Similarly, proximity to the single integrally protected area in the landscape maintained an overriding positive influence on elephant abundance, and logging roads (exploited by elephant poachers) had a major negative influence on the species' distribution (Stokes et al., 2010).

In our study area (DFR and buffer zone) we show that there are clear spatial differences in the distribution of threats. Areas outside the DFR are mostly affected by forest loss and, secondarily modified by fire. In contrast, wildlife risk areas, due to poaching, are concentrated inside the DFR, where high-diversity areas (according to the WI) overlap with zones where poaching occurs. However, the three threat models combined indicated that the areas outside the DFR (principally in the west but also in the north and the east, see Figure 2h) were the areas with the highest overall risk, with areas within the protected area itself presenting intermediate risk values. This is a consequence of integrating two threat factors that occur principally outside the DFR margins (i.e. forest loss and fire), and only one factor affecting the inside of the DFR (i.e. poaching).

Model-based approaches have clearly demonstrated that in Central Africa poaching and disease are the main threats affecting the survival of great apes, whereas poaching is the prime menace against elephants (Walsh et al., 2003; Stokes et al., 2010; Maisels et al., 2013; Fa et al., 2014; Wich et al., 2014; Critchlow et al., 2015; Gong et al., 2017; Strindberg et al., 2018). Such models are useful tools for determining the impact of anthropogenic disturbances on protected species on a broad biogeographical scale. However, unlike other commonly used SDM approaches, FF models and risk maps, as we show in this paper, can provide easily available rapid assessment tools to highlight the most vulnerable regions of species of conservation concern. Conservation managers and planners are able to use these maps to allow a more effective application of human and technical resources and implement more effective conservation measures. Although we have shown that data gathered in the field can be easily analysed beyond the SMART platform, the skills required to undertake modelling such as that performed in this study will require a different staff profile from those involved in the day-to-day running of a protected area. Currently, the application of spatial models to real situations is scarce, but we suggest that this may be possible by finding pragmatic, cost-effective ways in which modelling (and modellers) can be integrated in the team of experts involved with the management wildlife and protected areas. Data input, preparation, and analyses should be planned by modellers who can harness the growing volume of field and satellite-derived data to characterize levels of threat and distribution of wildlife to enable more agile protection of highly threatened species and spaces.

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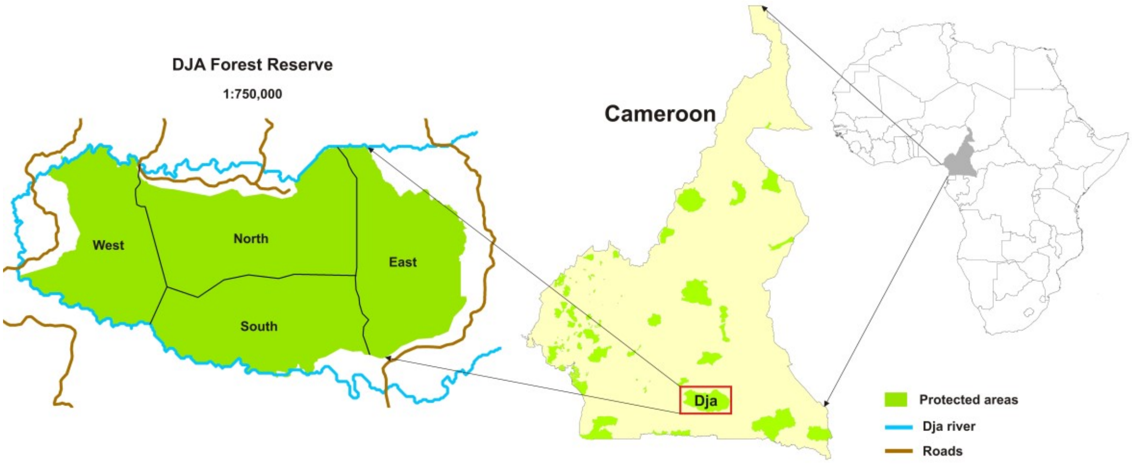
Fig, 1.



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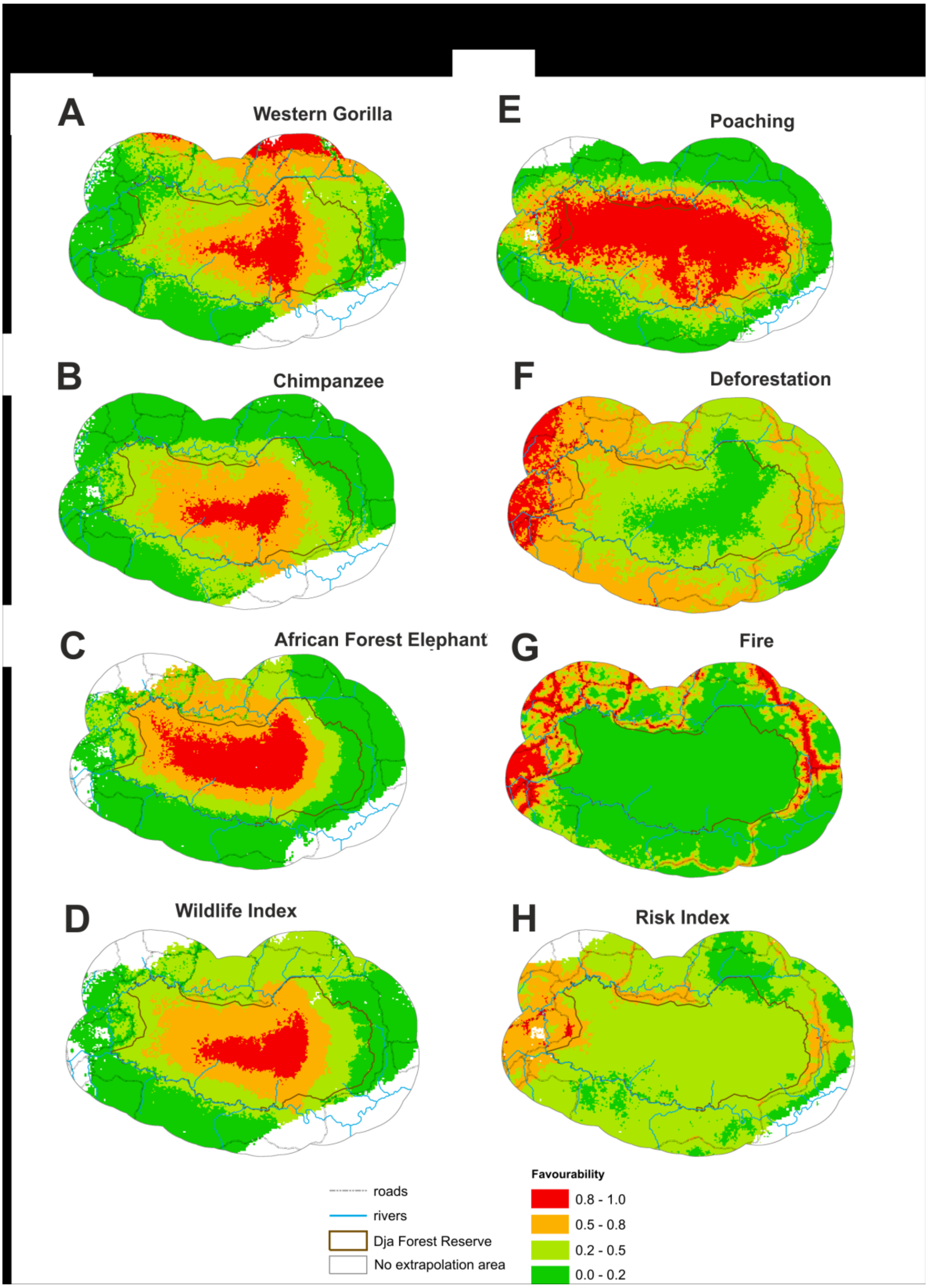
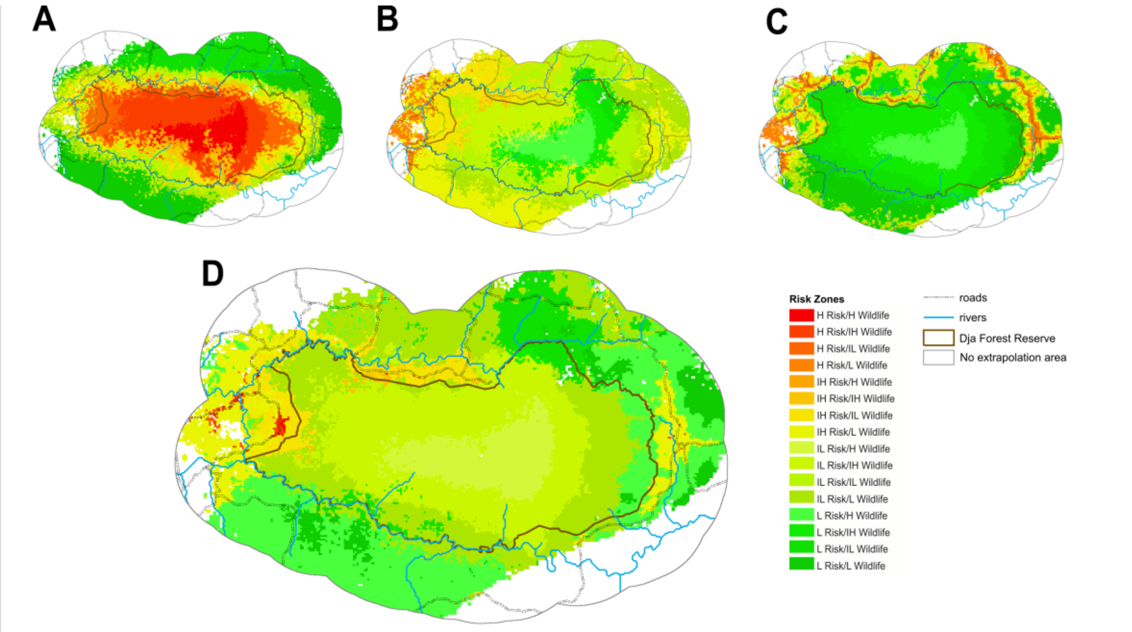

A
Western Gorilla
E
Poaching
B
Chimpanzee
F
Deforestation
C
African Forest Elephant
G
Fire
D
Wildlife Index
H
Risk Index
roads
rivers
Dja Forest Reserve
No extrapolation area
Favourability
0.8 - 1.0
0.5 - 0.8
0.2 - 0.5
0.0 - 0.2

Fig. 3.


A
B
C
D
Risk Zones
H Risk/H Wildlife
H Risk/IH Wildlife
H Risk/IL Wildlife
H Risk/L Wildlife
IH Risk/H Wildlife
IH Risk/IH Wildlife
IH Risk/IL Wildlife
IH Risk/L Wildlife
IL Risk/H Wildlife
IL Risk/IH Wildlife
IL Risk/IL Wildlife
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L Risk/IH Wildlife
L Risk/IL Wildlife
L Risk/L Wildlife
roads
rivers
Dja Forest Reserve
No extrapolation area

Fig. S1

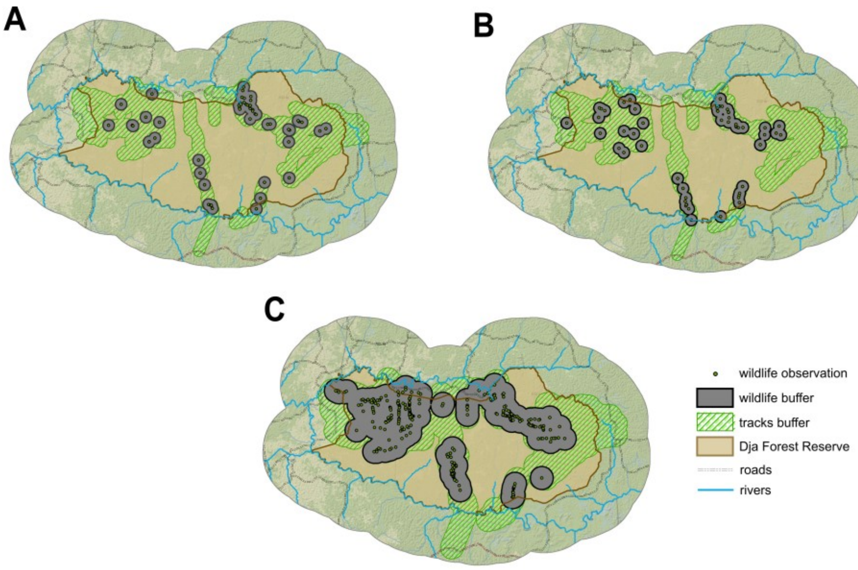
A
B
C
wildlife observation
wildlife buffer
tracks buffer
Dja Forest Reserve
roads
rivers

Fig. S2

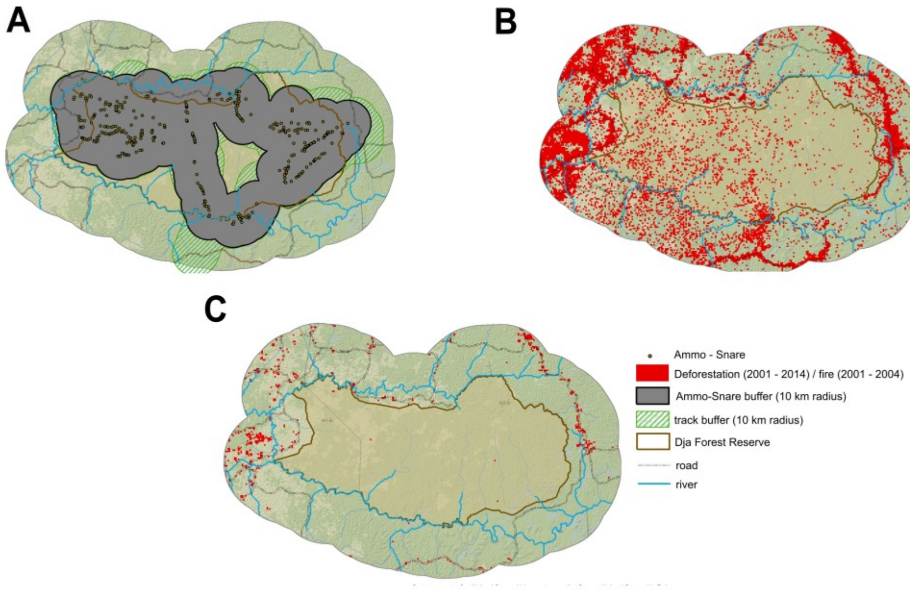
A
B
C
Ammo - Snare
Deforestation (2001 - 2014) / fire (2001 - 2004)
Ammo-Snare buffer (10 km radius)
track buffer (10 km radius)
Dja Forest Reserve
road
river

FIGURE LEGENDS

Figure 1. Location of the study area (Dja Forest Reserve), southern Cameroon.

Figure 2. Environmental favourability models projected to the whole study area for species and threats (favourability values: minimum = 0 and maximum = 1). The grey area was not considered for model projection, because the variables values in these squares were not represented in the model training area. a) Western Gorilla, b) Chimpanzee, c) African Forest Elephant, d) combined species, e) poaching, f) forest loss and g) fire and h) combined threats.

Figure 3. Map of risk for wildlife based on the combination of the Wildlife index and a) the threat of poaching (represented by favourable areas for ammunition and snare), b) threat of forest loss, c) threat of fire and d) three threats combined. High (H): index values ≥0.8. Intermediate-High (IH): index value between 0.5 and 0.8. Intermediate-Low (IL): index values between 0.5 and 0.2. Low (L): index values ≤ 0.2. The grey area was not considered for model projection.

Supplementary Figure 1. Area for model training (striped plus dark grey area) fixed for a) Western Gorilla, b) Chimpanzee and c) African Forest Elephant, and positive contacts (green points) surrounded by buffer areas suggesting presence of this species (dark grey).

Supplementary Figure 2. Area for model training fixed for a) poaching (striped plus green area), and observation of traps and ammunition cartridges (black points), surrounded by buffer areas suggesting occurrence of these objects (green); b) distribution of forest loss events in the study area (red squares) and c) distribution of fire events in the study area (red points).