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6 # Spatial modelling for predicting potential wildlife distributions and

7 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

67 Pfaff, 2011; Nelson and Chomitz, 2011; Tranquilli et al., 2014). The persistence

68 of wildlife in PAs ultimately depends on increasing conservation efforts to

69 combat such threats (Arcese et al., 1995; Jachmann and Billiouw 1997; Bruner

70 et al., 2001; de Merode and Cowlishaw, 2006; de Merode et al., 2007).

71

72   Law enforcement in PAs in the Congo Basin is notoriously underfinanced

73 (Wilkie et al., 2001). Thus, tools that enable the often, resource-limited (in

74 technology, weapons and personnel) site-based staff, to better patrol more

75 areas with greater regularity, have been developed recently. These have

76 resulted from the increased accessibility of geospatial technologies associated

77 with Global Positioning Satellites (GPS), remote sensing and Geographic

78 Information Systems (GIS) (O'Neil 2005). Two applications, CyberTracker and

79 SMART (Spatial Monitoring And Reporting Tool), are now available to improve

80 the effectiveness of wildlife law enforcement patrols and site-based

81 conservation activities on the ground. SMART contains a suite of programs that

82 can use mobile data collected with the CyberTracker App (CyberTracker, 2018).

83 CyberTracker operates within a GPS enabled mobile device e.g. smartphone or

84 a Personal Digital Assistant (PDA) to collect observation and GPS data in a

85 single unit. On return from their patrols, data collected by rangers as part of their

86 daily work (e.g. wildlife observations, poaching encounters) can be transferred

87 to directly into the SMART database in a semi-automated process. These tools

88 are open source and non-proprietary and are currently deployed in hundreds of

89 sites around the world. (Henson et al., 2016, SMART, 2017, 2018).

90

91   Spatial modelling of observation data gathered using CyberTracker and

92 SMART over a relevant period of time can be used to predict significant areas of

93 threats relative to areas of abundance of the target species across a PA

94 including in unpatrolled areas.   Increasing the probability of detecting illegal

95 activities improves the efficacy of PA law enforcement (Leader-Williams and

96 Milner-Gulland, 1993), leading managers to target areas where threats are most

97 likely to occur (Campbell and Hofer, 1995). Mapping and predictions of threat

98 occurrence can be effective in helping law enforcement reduce deforestation

99 threats (Linkie et al., 2010) and can result in cost-efficient prevention of illegal

100 activities (Plumptre et al., 2014).

101

102   In this paper, we focus attention on understanding the distribution of and

103   threats affecting the Endangered chimpanzee (*Pan troglodytes*), the Critically

104   Endangered Western lowland gorilla (*Gorilla gorilla gorilla*), and the Endangered

105   African forest elephant (*Loxodonta cyclotis*)[1] within the Dja Forest Reserve

106   (DFR) in southern Cameroon. The DFR is a key stronghold for these flagship

107   species and is one of Africa's most biodiverse rainforests. Despite its

108   importance, the state of conservation of the reserve is precarious, due to the

109   continuing impact of uncontrolled commercial hunting and other illegal activities.

110   As a result, the DFR is likely to be inscribed on the List of World Heritage in

111   Danger (UNESCO, 2018). A number of measures have been proposed to

112   strengthen the institutional and operational framework for management of the

113   DFR, including the strengthening of technical and logistical capacities

114   (UNESCO, 2018).

115

116   Adequate law enforcement patrolling within the DFR is restricted by the

117   terrain's inaccessibility and by the small (75-man) ranger force currently in

118   place. Given this situation, timely analyses of data gathered by these patrols

119   can be used to assist the ranger force become more strategic. Here, we utilise

120   patrol data on the distribution of the target species and pressures on these, to

121   generate maps of high-pressure areas for wildlife. These maps are created

122   using Favourability Function (FF) modelling (Real et al., 2006; Acevedo and

123   Real, 2012). FF is a procedure based on logistic regression that removes the

124   effect of species prevalence from presence probabilities, thus evening out

125   model predictions for different species and factors so that they can be directly

126   combined. FF modelling has been used to resolve species conservation issues

127   (e.g. Estrada et al., 2008; Fa et al., 2014). Based on the results of our

128   modelling we discuss possible management and conservations interventions

129   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).

164   In total, patrols covered 1,384 km over 192 patrol days (Dupain et al.,

165   2017). Each patrol team undertook 10-day missions within pre-determined

166   itineraries; routes were decided on the basis of knowledge of the terrain, but

167   were not randomly chosen. Data were gathered from 6h to 17h during patrol

168   days. Patrols would seize hunting gear and fraudulently collected products,

169   would destroy traps and camps, collect cartridges and other polluting objects,

170   and be involved in sensitization and eviction of offenders. Tracklogs, photos and

171   observations of mammals and human activities were georeferenced and

172   recorded. For this paper, we used only data of elephant dung, gorilla nests,

173   chimpanzee nests and encounters with hunting camps, poachers, cartridges

174   and snares.

175

176   All patrols (each composed of six guards, and four local village porters)

177   carried a PDA equipped with CyberTracker for download to a computer running

178   SMART. A total of 60 out of 75 eco-guards were trained in the use of the PDA

179   and to operate Cyber-Tracker and SMART; all data collection protocols were

180   approved by the Conservation Department in Cameroon.

181

182   2.3.   Modelling variables

183   Patrol observations data of the presence of the three species were used to

184   delimit the distribution of wildlife within the DFR. Threat data based on poaching

185   signs, forest loss and fires, the latter two derived from remote sensing, were

186   dependent variables in our models. Independent variables included spatial data

187   on environmental and anthropogenic factors obtained from non-field based

188   sources. Records for each variable were assigned to 0.5×0.5-km grid squares

189   covering the entire study area.

190

191   *Dependent variables*

192   We used presence records of chimpanzees, gorillas and elephants

193   gathered by DFR park personnel during 2015 and 2016. Park personnel

194   employed CyberTracker hand-held devices, allowing them to record

195   observations quickly and easily prior to upload into the fully compatible SMART

196   software. For each positive contact (Supplementary Figure 1), we fixed a 2.5 km

197   buffer zone for gorillas and chimpanzees, and 5.0 km for elephants. The size of

198   these buffer zones was based on the average daily distances travelled by each

199   species in Wilson and Mittermeier (2011) and Mittermeier et al. (2013). For

200   modelling purposes, we assumed that the species was present in all the

201   0.5×0.5-km squares included within these buffers.

202

203   Data on poaching consisted of geo-referenced records of traps and

204   ammunition cartridges found by the DFR staff during their patrols. We assumed

205   that poachers were active within a maximum of a 10-km radius buffer around

206   each record from data on the area covered by trappers in Equatorial Guinea

207   (Kümpel, 2006).

208

209   Forest loss within 0.5×0.5-km squares was derived from comparisons of

210   newly deforested areas between 2001 and 2014 (i.e. a 15-year period prior to

211   our wildlife evaluation) available from Hansen (2013) and from the Global Forest

212   Change web site (https://earthenginepartners.appspot.com/science2013-global-

213   forest). Fire presence was defined as all 0.5×0.5-km squares containing active

214   fire observations between 2001 and 2014 in NASA's FIRMS database

215   (https://firms.modaps.eosdis.nasa.gov) (Supplementary Figure 2).

216

217   Absences for all variables based on field personnel observations (i.e.

218   wildlife and poaching) were defined as all non-presence in 0.5×0.5-km squares

219   within a buffer area around the tracks followed by ranger patrols

220   (Supplementary Figure 1 and Supplementary Figure 2a). This minimized bias

221   caused by uneven sampling throughout the study area since models are initially

222   developed within the regions of the study area that were sampled by ranger

223   patrols. Buffer width was specific to every variable, according to the above.

224   Using this criterion, there were 2,388 presences and 7,994 absences for

225   gorillas, 2,630 presences and 7,752 absences for chimpanzees, 8,542

226   presences and 6,503 absences for elephants as well as 20,858 presences and

227   3,047 absences for poaching. For forest loss and fire, all non-presence

228   0.5×0.5km squares within the study area were considered as absences, given

229   the unbiased nature of remote sensing observations.

230

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

297 discrimination capacity of the models (Lobo et al., 2008). The significance of

298 every independent variable in the model was assessed using the Wald test.

299

300 *Model extrapolation*

301 Wildlife and threat of poaching models, fitted in training areas constrained

302 to buffers around ranger patrol tracks, were extrapolated to the whole of the

303 study area using the following equation (Real et al., 2006):

304

305 $$F = e^y/[(n_1/n_0) + e^y]$$

306

307 where n_1 and n_0 are presence and absence numbers within the training area, e

308 is the base of the natural logarithms, and y is the linear combination of predictor

309 variables (i.e. the logit) of the logistic regression defining P (see above).

310

311 Model extrapolations were made only to the 0.5×0.5-km squares whose

312 variable values were within the dominion of the Favourability Function, i.e. were

313 in the range of values shown by the model variables within the training area. We

314 only accepted a 10% tolerance above and below. This precaution avoided

315 projections to zones that were not environmentally represented in the area used

316 for model training.

317

318 2.5.   Wildlife and risk maps

319 In this paper we define threat as an action (poaching, fire, forest loss)

320 likely to cause damage, harm or loss. We define risk as the potential or

321 possibility of an adverse consequence resulting from the combined effects of

322 one or more threats.

323

324 Using the average of favourability models obtained for the three target

325 species we calculated a "Wildlife Index (WI)". A "Threat Index (TI)" was derived

326 from the average of the three threat models. We employed the average rather

327 than the sum so as to maintain the range of resulting values between 0 and 1.

328 We combined the threat and wildlife indices to derive an overall map (which we

329 call a risk map) to show where wildlife was more likely to be affected by threats

330 either separately or combined. We divided the study area by the following

331 favourability values for each index: High (H): index values ≥0.8.

332 IntermediateHigh (IH): indices values between 0.5 and 0.8. Intermediate-Low

333 (IL): indices values between 0.5 and 0.2. Low (L): indices values ≤ 0.2.

334

335 **3.   Results**

336 3.1.   Wildlife models

337   We obtained significant favourability models for all three species (Table 1,

338 Figure 2). These models had acceptable values of discrimination capacity (AUC

339 >0.745), and fair classification capacity values (Cohen's Kappa value >0.300)

340 as shown in Table 2. All showed a fairly high proportion of correctly classified

341 presences and absences; values being ≥0.635 for sensitivity and specificity.

342 The correct classification rate was always ≥0.670.

343

344   **Table 1 and 2 around here**

345

346   Greater distances to the nearest road were associated with higher

347 favourability for the presence of all species, but larger distances from towns and

348 villages were also significantly related to more favourable areas for gorillas.

349 Maps showed that highly favourable areas within the core of the DFR were

350 typical for all three species. Highly favourable areas for gorillas and elephants

351 were also found along the northern part of the DFR (Figure 2a, 2c), but not for

352 chimpanzees (Figure 2b). The latter species had highly favourable areas along

353 the south-eastern area of the park as well as in the central region. Overall,

354 larger highly favourable areas within the centre of the DFR were more typical for

355 elephants (Figure 2c) than for the other two species. For all three species

356 combined, more favourable areas were within the interior of the DFR (Figure

357 2d), with less favourable areas along a ring from the west to the east of the

358 park.

359

360 3.2.   Threat models

361   Significant favourability models were also obtained for the three threat

362 variables considered in this study (Table 3). Discrimination capacity was

363   acceptable (AUC >0.749; Table 2) but classification capacity was low for fire

364   (Kappa = 0.088), moderate for poaching (Kappa = 0.422) and fair for

365   deforestation (Kappa = 0.269). The three models showed a fairly high

366   proportion of correctly classified presences and absences (sensitivity and

367   specificity values were always ≥0.685).

368

369   **Table 3 around here**

370

371   Proximity to roads and to towns and villages were significantly related to

372   high favourability values for forest loss and fire; proximity to agriculture was also

373   relevant. However, environmental variables defining high favourability for

374   poaching were a combination of climatic variables (mainly high precipitation in

375   the wettest month and low precipitation in the warmest quarter),

376   topohydrography (greater distance from navigable streams) and soil (low sand

377   percentage). Favourable areas for poaching were largely concentrated around

378   the centre of the reserve (Figure 2e), but favourable areas for forest loss and

379   fires were found outside the DFR (Figure 2f, 2g). The combined TI (Figure 2h)

380   indicated that areas that were most favourable for all threats were along the

381   western boundary and to a lesser extent just outside the eastern border of the

382   DFR.

383

384   3.3.   Combining wildlife and threat models

385   TI-WI maps for each threat factor indicated that the more favourable areas

386   for poaching actually overlapped considerably with the more favourable areas

387   for wildlife, in fact occupying most of the DFR (Figure 3a). In contrast, the

388   highest risk from forest loss and fires were concentrated along the western

389   region of the study area, but always outside the DFR (Figure 3b, 3c).

390

391   The combined TI-WI map showed that the highest levels of risk for wildlife

392   were found along the western and the northern sectors of the DFR (Figure 3d).

393   Along the east of the DFR, high-risk areas are found just outside the park.

394

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.

427 Favourability provides commensurate values and is independent from presence

428 prevalence (Acevedo and Real, 2012). Such characteristics are particularly

429 useful in conservation biology such as in defining areas where a group of

430 species may be more vulnerable to different factors (Fa et al., 2014) or when

431 models for a large number of species need to be combined to define relevant

432 areas for conservation (Estrada-Peña et al., 2008). In this paper, we apply FF

433 modelling which is an approach that has advantages over other more widely

434 used spatial methods (see Olivero et al., 2016; Acevedo and Real, 2012). FF

435 like logistic regression relies on assumptions such as the independence of

436 observations, and limited multicollinearty which are not always restricted met.

437 We show how ranger and satellite data can be effectively overlaid to model the

438 distribution of animal species of conservation interest, to determine areas likely

439 to be more at risk from poaching and other anthropogenic factors.

440

441   Scarce technical and human resources and inadequate resource

442 management are among the main reasons for the decline in wild populations of

443 many threatened large mammal species across the Congo Basin, both inside

444 and outside protected areas (Campbell et al., 2008; Kühl et al., 2017). Because

445 of this, the more effective application of existing resources could benefit from

446 the use of suitable tools for wildlife management and conservation. In this study,

447 we propose a conservation biogeography approach to assist in the protection of

448 wild populations of three threatened, iconic African mammal species. Our

449 models clearly suggest that the most favourable areas for gorillas, chimpanzees

450 and elephants are found within the core of the studied protected area, the DFR.

451 According to this, isolation is a highly relevant factor, since the most important

452 variable explaining the presence of the three species in our wildlife models was

453 "distance to roads". This also explains why large areas located within the core

454 of the DFR, at least during our study period, are highly favourable for the three

455 species (Figure 4). These results are corroborated by field work undertaken by

456 one of our authors, (JD) who undertook a transect of 98 km through the middle

457 of the DFR, and who found higher levels of wildlife signs, particularly of

458 elephants, within the core of the reserve (Dupain et al., 2017). Our models

459 clearly suggest that favourable areas for poaching, as expected, correspond

460 with the more favourable areas for wildlife. In both cases, areas that are more

461 distant from roads, from navigable rivers and from human settlements, hence

462 more remote, were more favourable to poaching and wildlife. Also, these areas,

463 primarily along the north-western region of the reserve, are those with a higher

464 proportion of soil. This may point to the fact that more sandy soils are linked to

465 poorer forests, in terms of plant and animal diversity, so naturally poachers are

466 likely to search for animals to hunt in remote forests in deeper soils.

467

468 Our results confirm the findings of regional analyses of the spatial

469 relationship between the distribution of gorillas, chimpanzees and elephants and

470 human activities in other parts of the Congo Basin (Stokes et al., 2010; Maisels

471 et al., 2013; Strindberg et al., 2018). In the case of the great apes, Strindberg

472 et al. (2018) showed that human-related variables (in particular distance to

473 roads and human population densities) as well as canopy height and Ebola

474 (natural variables) were important predictors of great ape density and

475 distribution.   Stokes et al. (2010) also indicated that chimpanzees show a clear

476 preference for unlogged or more mature forests and human disturbance had a

477 negative influence on chimpanzee abundance, in spite of anti-poaching

478 interventions. Similarly, proximity to the single integrally protected area in the

479 landscape maintained an overriding positive influence on elephant abundance,

480 and logging roads (exploited by elephant poachers) had a major negative

481 influence on the species' distribution (Stokes et al., 2010).

482

483 In our study area (DFR and buffer zone) we show that there are clear

484 spatial differences in the distribution of threats. Areas outside the DFR are

485 mostly affected by forest loss and, secondarily modified by fire. In contrast,

486 wildlife risk areas, due to poaching, are concentrated inside the DFR, where

487 high-diversity areas (according to the WI) overlap with zones where poaching

488 occurs. However, the three threat models combined indicated that the areas

489 outside the DFR (principally in the west but also in the north and the east, see

490 Figure 2h) were the areas with the highest overall risk, with areas within the

491 protected area itself presenting intermediate risk values. This is a consequence

492   of integrating two threat factors that occur principally outside the DFR margins

493   (i.e. forest loss and fire), and only one factor affecting the inside of the DFR (i.e.

494   poaching).

495

496   Model-based approaches have clearly demonstrated that in Central Africa

497   poaching and disease are the main threats affecting the survival of great apes,

498   whereas poaching is the prime menace against elephants (Walsh et al., 2003;

499   Stokes et al., 2010; Maisels et al., 2013; Fa et al., 2014; Wich et al., 2014;

500   Critchlow et al., 2015; Gong et al., 2017; Strindberg et al., 2018). Such models

501   are useful tools for determining the impact of anthropogenic disturbances on

502   protected species on a broad biogeographical scale. However, unlike other

503   commonly used SDM approaches, FF models and risk maps, as we show in this

504   paper, can provide easily available rapid assessment tools to highlight the most

505   vulnerable regions of species of conservation concern. Conservation managers

506   and planners are able to use these maps to allow a more effective application of

507   human and technical resources and implement more effective conservation

508   measures. Although we have shown that data gathered in the field can be easily

509   analysed beyond the SMART platform, the skills required to undertake

510   modelling such as that performed in this study will require a different staff profile

511   from those involved in the day-to-day running of a protected area. Currently, the

512   application of spatial models to real situations is scarce, but we suggest that this

513   may be possible by finding pragmatic, cost-effective ways in which modelling

514   (and modellers) can be integrated in the team of experts involved with the

515   management wildlife and protected areas. Data input, preparation, and

516   analyses should be planned by modellers who can harness the growing volume

517   of field and satellite-derived data to characterize levels of threat and distribution

518   of wildlife to enable more agile protection of highly threatened species and

519   spaces.

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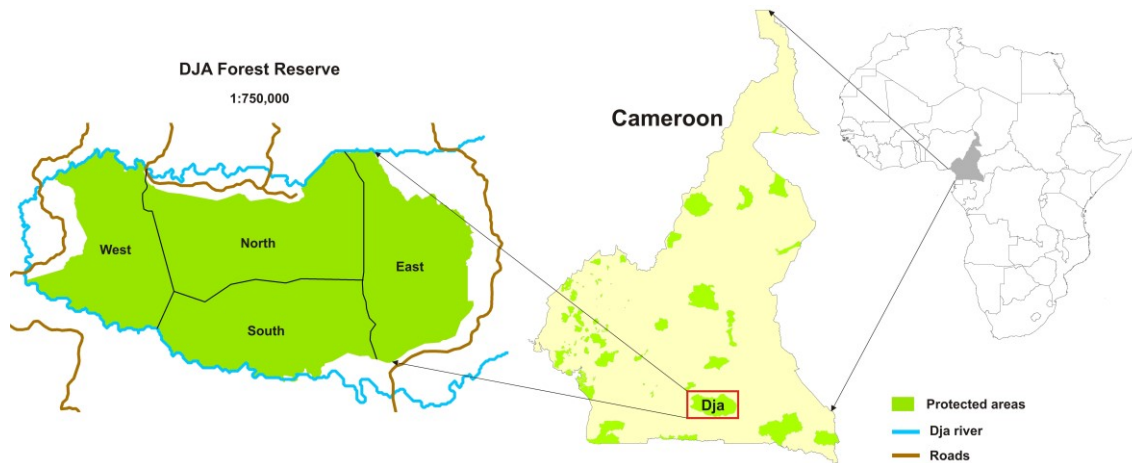717   Vol 2. Hoofed Mammals. Lynx Edicions, Barcelona.

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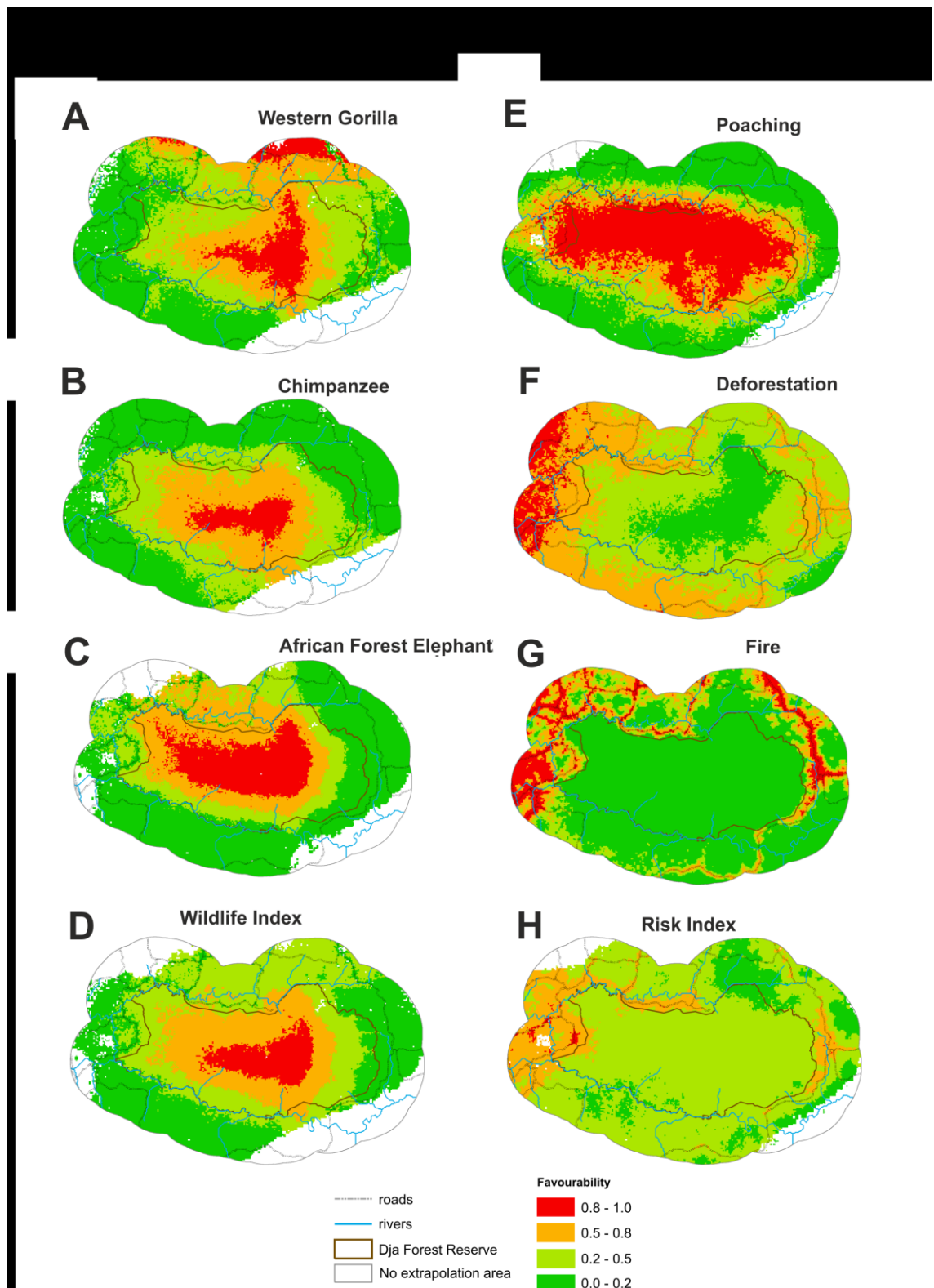
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728 **Fig, 1.**

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750 **Fig. 2.**

A Western Gorilla
B Chimpanzee
C African Forest Elephant
D Wildlife Index
E Poaching
F Deforestation
G Fire
H Risk Index

roads
rivers
Dja Forest Reserve
No extrapolation area
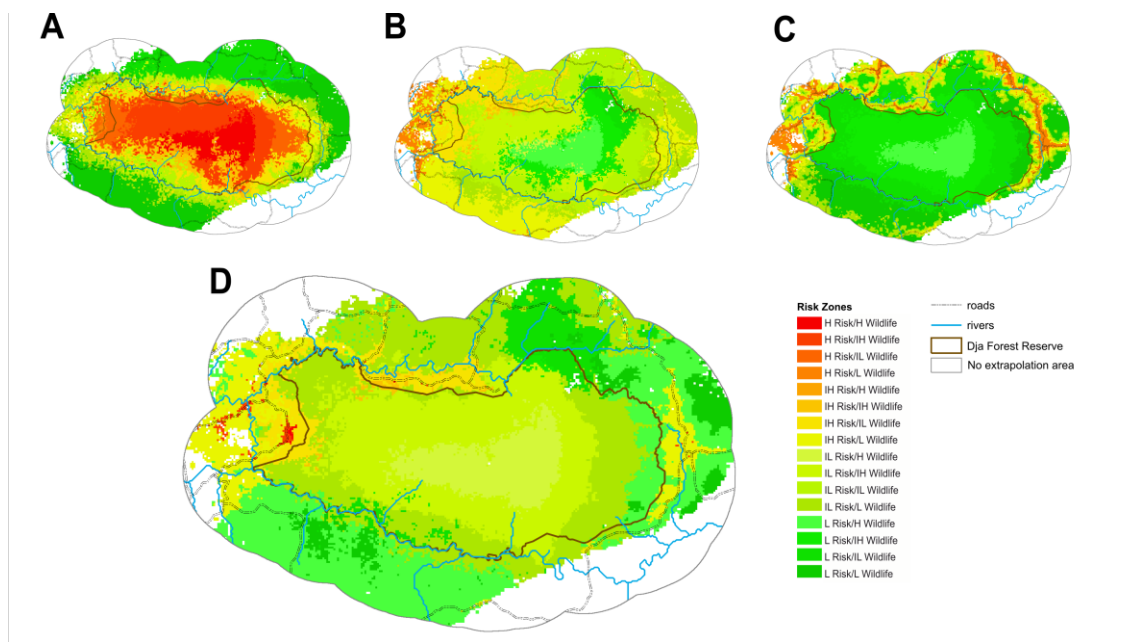
Favourability
0.8 - 1.0
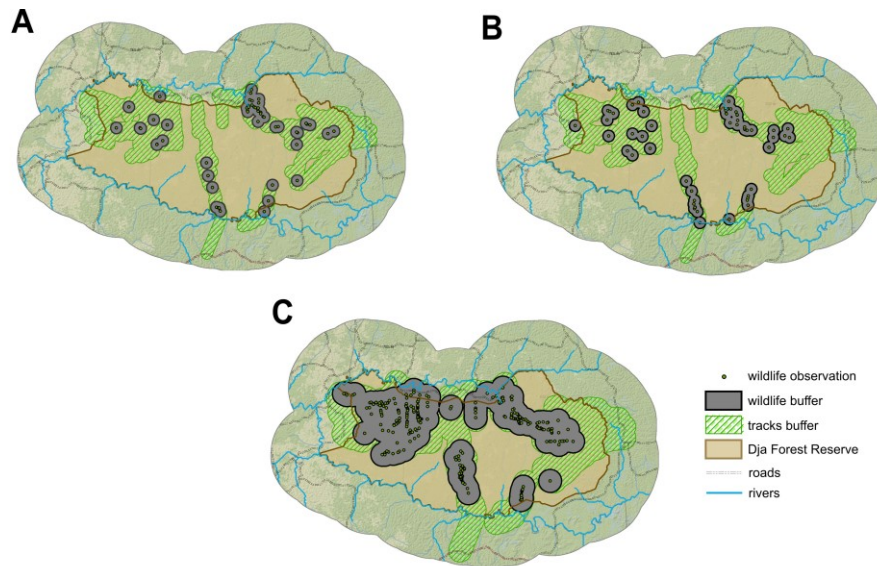0.5 - 0.8
0.2 - 0.5
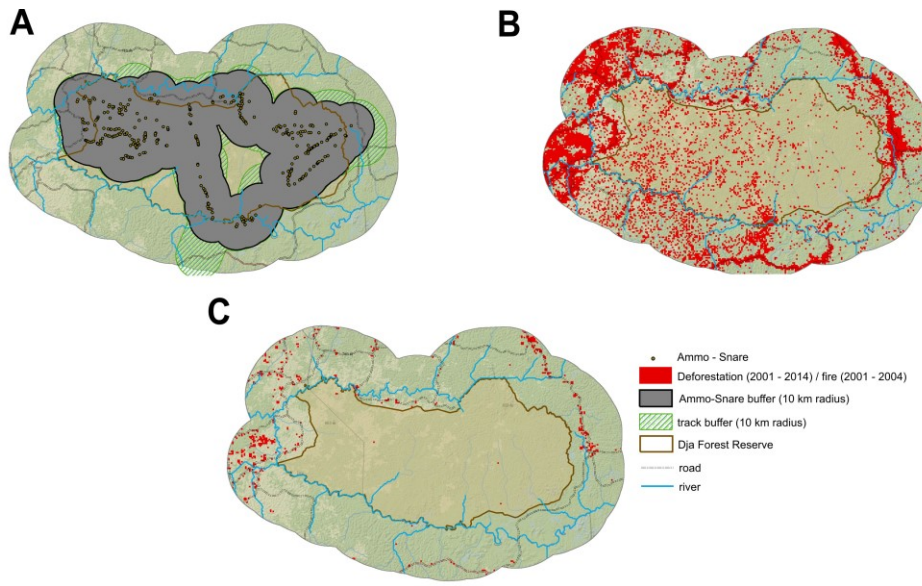0.0 - 0.2

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754 **Fig. 3.**

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773 **Fig. S1**

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Fig. S2

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).