Planning for Palm Oil:
Are We Saving Wildlife by Saving Carbon?

by

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Executive Summary

Palm oil has become the most widely traded vegetable oil in the world. This has led to mass conversion of forests to monoculture plantations across the tropics, negatively impacting carbon stocks and wildlife habitat. As palm oil continues to spread, countries like Gabon are attempting to mitigate the negative impacts of palm oil plantations by planning their establishment in low carbon stock areas. This approach alleviates the effects of palm oil on carbon stocks, yet does not take into consideration the impact on wildlife. Using a proposed palm oil concession site in Gabon, this study explored the relationship between carbon stocks and forest elephant density as well as carbon stocks and predicted forest elephant habitat. We asked the question – does preserving high carbon areas also protect forest elephant habitat? To answer this question, we first identified areas of high carbon by using data collected in the field to calibrate LiDAR data across the study site. Next, using data from wildlife surveys, we calculated forest elephant dung density. We then built two different models to examine elephant distributions across the clusters: (1) a kernel density estimator (KDE) to model the density of elephant dung, and (2) a species distribution model to predict elephant habitat (SDM). Finally, to examine the relationship between aboveground biomass (AGB) and forest elephant abundance, we correlated the results of both models (dung density and probability of being elephant habitat) with AGB at 400 randomly chosen points. In both cases, the relationship between AGB and elephant abundance was weak. While there was some overlap of high carbon areas and forest elephant habitat, approximately one third of the existing forest elephant habitat in the study site is at risk of conversion to palm oil when only high carbon areas are protected. When planning for palm oil in Central Africa, both carbon stocks and forest elephant habitat must be taken into consideration separately: protecting one does not necessarily protect the other. With careful land use planning, the ability to mitigate some of the negative impacts of palm oil on carbon stocks and wildlife habitat is possible. More studies are needed to understand the overlap between high carbon stock areas and the habit of other wildlife species, as well as how wildlife adapt (or do not adapt) to palm oil agriculture in Central Africa.

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1. INTRODUCTION

1.1 Palm Oil Agriculture

Palm oil agriculture has spread rapidly across the tropics causing large-scale forest conversion with accompanying losses of both carbon stocks and biodiversity (Smit *et al.,* 2013, Meijaard and Sheil 2013, Fitzherbert *et al.,* 2008). In the past, the agricultural boom has been concentrated in Southeast Asia, but growing demand for palm oil is predicted to drive its expansion in Central Africa over the coming decade (Wilcove and Koh, 2010; Amigun *et al.,* 2011). As the second largest contiguous rainforest in the world, Central Africa's vast carbon stocks and unique biodiversity are under threat with an estimated ten million hectares of rainforest already converted or being considered for conversion to palm oil plantations (Wich *et al.,* 2014; Carrere, 2013).

High carbon emissions from conversion of forested land to palm plantations are associated with both smallholder enterprises and large-scale industrial agriculture in the tropics (Hansen *et al.,* 2014; Lee *et al.,* 2014). In Indonesia alone, it is estimated that palm oil plantations contributed on average, 216 to 268 million tons of carbon emissions from 2001-2010 (Carlson and Curran, 2013). While some wildlife thrive in palm oil plantations, wildlife biodiversity as a whole decreases (Jennings *et al.,* 2015; Meijaard and Sheil, 2013). The negative impacts palm oil has had on wildlife biodiversity in Asia and Indonesia are expected to proliferate in Central Africa (Oberle, 2015; Wich *et al.,* 2014).

Gabon is considered the second most forested tropical country in the world, with an estimated 85% of its land covered in forest (Sannier *et al.,* 2014). The country has enjoyed relative stability and economic growth due in large part to its offshore crude oil reserves (Jones, 2013). With suitable environmental conditions for palm oil production and a growing market for oil, palm agriculture has become a natural addition to Gabon's export portfolio (Edou Nguema *et al.,* 2008). Currently the country has plans to develop over 300,000 ha of oil palm plantations, which would occur over 1.2% of its land mass (Gabon, 2014). While the country's goal is to become the top producer of palm oil in Central Africa, the cost to its carbon stocks and wildlife habitat could be tremendous. Of great concern is the status of forest elephants (*Loxodonta cyclotis*),

which are undergoing large losses to poaching (Breuer *et al.,* 2016; Maisels *et al.,* 2013). Gabon is home to the largest population of forest elephant in Central Africa, but industrial palm agriculture could further reduce available habitat for the species and provide greater hunting access to forests (Maisels *et al.,* 2013; Lewis *et al.,* 2015).

In an attempt to minimize the negative effects of palm oil agriculture, Gabon has reached an agreement with agricultural companies to produce Roundtable on Sustainable Palm Oil (RSPO) certified palm oil in the country (Gabon, 2014). RSPO certification is a voluntary certification program that aims to monitor both the social and environmental impacts of palm oil agriculture (RSPO, 2013). Standards for certification are country specific, with the country of production setting the requirements that a company must meet for certification. Once certified, palm oil companies can market their product at a premium. Gabon is in the process of defining standards for RSPO certification, with the expectation that certified agriculture will reduce the carbon emissions from the conversion of forested areas to palm oil plantations (Gabon, 2014).

1.2 Study Objectives

Conservation is maximized when multiple ecosystem services, such as carbon storage and wildlife, can be preserved at the same time. While wildlife has been shown to benefit carbon storage (Peres *et al.,* 2016), here we ask whether protecting areas of high carbon has the potential to also protect threatened species habitat. Few studies have examined the overlap in these two important conservation priorities. We use a proposed palm oil concession site in Gabon to ask the question: does conserving high carbon forest simultaneously protect forest elephant populations? To do so, we identify high carbon areas using remotely sensed LiDAR data calibrated with field plot measurements. Next, using kernel density estimator (KDE) analysis we map forest elephant dung density and using species distribution modeling (SDM), we map forest elephant habitat. Lastly, we examine the relationship between aboveground biomass (AGB) and forest elephant dung density and habitat using.

2. METHODS

2.1 Study Site and Overview

This study was conducted within two sites set aside by the government of Gabon (115,676 ha of land) for palm oil production: the Ekouk cluster (83,053 ha) and the Massika cluster (32,623 ha; Figure 1). Both clusters are located in the provinces of Estuaire and Moyen Ogooue in the coastal sedimentary basin. The climate in the area is equatorial with the principal soil types for the Ekouk cluster being ferralic cambisols, orthic ferralsols, ferralic arensols and gleyic acrisols. The principal soil types for the Massika cluster are ferralic arensols, xantic ferralsols, luvic arenosols, ferralic cambisols, dystric gleysols, and dystric fluvisols (FAO *et al.*, 2012).

This study consists of four main steps, which are explained in detail below. First, to identify high carbon areas, we use field measurements of trees to calculate estimates of aboveground biomass (AGB) for 36 1-ha plots. We calibrate remotely sensed aerial LiDAR (Light Detection and Ranging) with the field measurements to estimate and map the density of carbon within both clusters. From this carbon map, we identify high carbon stock areas (HCS). Second, we estimate elephant dung densities across the study area and map dung density using kernel density estimator (KDE) analysis. Third, we predict forest elephant habitat across the study area using species distribution modeling. Fourth, we evaluate the relationship between AGB and dung density as well as the relationship between AGB and predicted forest elephant habitat using polynomial regression models.

2.2 Field-based Estimates of Aboveground Biomass

Within the clusters, we used a stratified-random design to position 37 plots to ensure unbiased sampling of the forest, with 26 plots planned for the Ekouk cluster and 9 plots planned for the Massika cluster (Figure 1). Field teams from the Gabon National Park Agency (ANPN) collected data from the 1-ha plots (100 x 100 m) between April and November 2015. All teams were trained in internationally recognized RAINFOR protocols for plot establishment and measurement (Phillips *et al.,* 2015). The teams established each plot and then inventoried and measured each tree with a DBH greater than 10 cm. Trees were identified to species level if known. The heights of 10 trees within 5 different DBH classes (10-20 cm, 21-30 cm, 31-40 cm, 41-50 cm and > 50 cm) and the five tallest trees in the plot were measured using a laser hypsometer (N = 55).

It is assumed that the total carbon stored in the forest is 50% of the above AGB (Chave *et al.,* 2014). To calculate AGB, height must first be estimated for all of the trees whose height was not measured in the field. To calculate the height of the unmeasured trees, we developed a regression equation relating diameter to height for each plot. We then used the pantropical equation from Chave *et al.* (2014) to calculate AGB for each plot:

$$AGB_F = \frac{1}{A} \sum_{i=1}^{N} 0.0673 \times \left(\rho_i \times D_i^2 \times H_i \right)^{0.976}$$

where *A* is the area of the plot and *N* is the number of trees >10 cm in diameter found in each plot. p_i is the wood density in g/cm^3, calculated by matching the tree species/genus/family with the global database of wood densities (Zanne *et al.,* 2009). If the tree was unidentified, it was given the mean wood density value of the plot. D_i is the tree DBH in cm collected in the field and H_i is the tree height in meters and is estimated using the methods mentioned above.

2.3 Landscape Estimate of Aboveground Biomass and Carbon Emissions

Remote sensing, like airborne LiDAR, allows the mapping of forest biomass and carbon across large areas at fine spatial resolution. For aerial LiDAR, a plane-mounted laser shoots pulses at the ground, and the return pulses are measured by a sensor on the place. The data can then be represented as a 3D cloud of points to create maps of the terrain and forest canopy height (Wulder *et al.,* 2012). By calibrating LiDAR with ground-truthed field plots, values of biomass and carbon can be extrapolated across the study area (Asner *et al.,* 2012).

Aerial LiDAR was flown over the Ekouk and Massika clusters from May to October 2015 by the French company IMAO. The raw LiDAR files were combined into a LAS Dataset for processing in ArcMap. The 3D Analysis Toolbox within ArcGIS was used to create a 5m digital terrain raster (DTM), and rasters for the first, second, and third returns, as well as all returns combined (DSM). We then created canopy height maps by subtracting the DTM from the DSM for the first, second, third and all returns.

To derive metrics for each of the tree plots, we clipped rasters to the plot boundaries, and then calculated the mean, standard deviation, maximum, minimum and range of height for returns 1, 2, 3 and all returns combined. We also calculated height percentiles (90th, 75th, 50th, 25th, 10th) for the first through third returns and all returns combined following Burton *et al.,* (in press).

To avoid multicollinearity, we evaluated pairwise correlations among all our derived metrics. For any highly correlated metrics ($|r| \geq 0.7$) we retained only the variable that had the highest correlation with plot AGB (Dormann *et al.,* 2013). We then constructed a linear regression model to examine the relationship between plot AGB and the remaining LiDAR metrics, and used a backwards selection process to reduce the full model to the most parsimonious model, using the Akaike Information Criterion (AIC) to compete models. To predict AGB across the entire study area, the final regression model was applied to a geographically centered 1 ha (100 x 100 m) focal area.

We predicted total carbon emissions that would result from the conversion of the clusters to oil palm plantation using the following equation (Burton *et al.,* in press):

$$Emissions\ Tg\ CO_{2\ eq} = \left(\begin{matrix} Forest \\ conversion \end{matrix} + \begin{matrix} Forest \\ sequestration \end{matrix} - \begin{matrix} Oil\ palm \\ sequestration \end{matrix} - \begin{matrix} HCS\ area \\ sequestration \end{matrix} \right) \times \left(\frac{Tg\ CO_{2\ eq}}{Tg\ C} \right)$$

We used a carbon sequestration rate of 2.41 Mg C ha^{-1} yr^{-1} for logged forest and a mean time-averaged sequestration of 36 Mg C ha^{-1} for palm oil with a 25-year rotation (Gourlet-Fleury *et al.,* 2013; Agus *et al.,* 2013).

Areas of high carbon were identified as having more than 118 Mg C ha^{-1} (Burton *et al.,* in press). We buffered areas of high carbon by 100 m to protect them from potential edge effects (Berenguer *et al.*, 2014). Once buffered, locations within each cluster that had greater than 50% high carbon plus buffer area were considered HCS areas. HCS areas were set aside to help offset the carbon emissions created from converting the rainforest to palm oil with a goal of reaching net zero carbon loss over a 25-year period.

2.4 Faunal Surveys

The field teams collected data on wildlife using conventional distance sampling methods where observers walk transects and measure the perpendicular distance from the transect to the observation (Buckland *et al.,* 2001). Wildlife surveys were conducted along 2-km linear transects. Every inventory plot had one transect running alongside it with 1-3 more transects planned 4 km away from the plot corners. Along each transect, field technicians collected data on direct (visual sitings or vocalizations of animals) and indirect observations (animal sign including dung, nests, and paths) of wildlife. The teams recorded GPS coordinates every 200 m along each of the 2-km transects. Other information such as terrain condition (i.e., slope, streams, swamp, etc.) and vegetation type (i.e., primary forest, degraded lands, etc.) were also recorded.

2.5 Abundance and Density of Forest Elephants

Distance sampling and analysis is a robust method for estimating species abundances for areas where the detection of observations is considered difficult, such as the dense tropical jungles of Gabon (Katsanevakis, 2007). Distance sampling incorporates a detection function that estimates the probability of an observation with distance from the transect (Buckland *et al.,* 2001).

We fitted 4 detection functions to the data: hazard-rate + cosine adjustment, hazard-rate + half-normal, uniform + cosine adjustment, and uniform + polynomial adjustment. The best model was selected on the basis of the lowest AIC. Model fit was examined with chi-square goodness-of-fit tests. To convert the density of animal sign into density of animals, we multiplied the dung density by the species-specific defecation rate and dung decay rate, using three common rates found in the literature.

To visualize the densities of forest elephant dung across the landscape, we applied a kernel density estimator (KDE) using the dung observations collected during transect surveying. KDE has been reliably used as a density estimator for over half a century (Silverman, 1986) and involves fitting a curved surface over each observation point in geographic space. As the distance from the observation increases, a lower value is given to each raster cell until it diminishes to zero. The value of each raster cell is the sum of all of the kernel surfaces that are within that cell.

2.6 *Species Distribution Modeling*

Monitoring forest elephants has proven to be difficult in the dense jungles of central Africa (Walsh and White, 1999). Understanding what factors drive forest elephant habitat selection is crucial to their conservation and management. Species distribution modeling (SDM) has become a popular tool in conservation because of its ability to explain a species' environmental tolerances and/or habitat preferences (Franklin, 2013; Guisan *et al.,* 2013). This is accomplished through the correlation of species presence and absence across a landscape with a set of predictor variables (Guillera-Arroita *et al.,* 2015). The development of a SDM involves the collection of species observation data, selection of explanatory variables, and model selection and implementation. The final product of a SDM analysis is a prediction map showing the probability of species occurrence extrapolated across the landscape.

Forest elephant habitat was modeled as a binary distribution using presence and absence data of dung collected during transect sampling. Transects were divided into 90 meter segments where segments with dung were considered presences and transects without dung were considered absences. During exploratory data analysis, we examined bivariate correlations among twelve predictor variables to reduce multicollinearity (Table S1). Predictor variables were considered strongly correlated when $|r| > 0.7$ (Dormann *et al.,* 2012), and we removed the predictor variable that had the weakest correlation with the response variable (dung presence and absence).

Once we had eliminated highly correlated variables, we evaluated the drivers of elephant presence and absence with generalized additive models (GAM) to allow for non-linear relationships among the response and predictor variables. In the GAM models, we used a binomial distribution with a log link function, and applied the same smoothing parameter to each coefficient for model simplicity (Wood and Augustin, 2002; Merow *et al.,* 2014). A full GAM model was constructed using the variables chosen during exploratory data analysis. From this full model, the independent variable that had the least significant explanatory power was removed. We used a backwards model selection process to find the most parsimonious model. The final model estimates the probability that an area is suitable forest elephant habitat, and can be applied to the entire landscape.

To categorize the landscape as suitable forest elephant habitat and unsuitable forest elephant habitat, we maximized the true positive rate of model prediction (sensitivity). Sensitivity is the measure of how often the model correctly predicts an observation as being in suitable forest elephant habitat. The mean probability method within the PresenceAbsence package was used to classify areas as suitable habitat versus unsuitable habitat based on a cutoff probability value (Freeman and Moisen, 2008). The sensitivity was analyzed using an exact one-tailed binomial test of significance. This test of significance allows us to test if the model accurately classify presences better than random guessing.

2.7 *Comparison between Aboveground Biomass and Forest Elephant Density and Habitat*

To understand the relationship between forest AGB and the density of forest elephant dung and predicted forest elephant habitat, we generated 400 random points across the study area (Figure S1). We calculated forest AGB, elephant dung density and the probability of that location being suitable forest elephant habitat for each sample point.

Using a polynomial regression model, we evaluated the relationship between the predictor variable, AGB, and the response variable, forest elephant dung density. To determine the relationship between AGB and the probability of a location being suitable forest elephant habitat, we built a second polynomial regression model with AGB as the predictor variable and the probability of a location being suitable forest elephant habitat as the response variable. All data were analyzed using ArcMap v. 10.3.1 (ESRI, 2015) and R v.3.2.1 (R Core Team, 2015).

3. RESULTS

3.1 Field-based Estimates of Aboveground Biomass

Of the 37 plots planned, 36 plots were established with 27 plots established in the Ekouk cluster and 9 plots established in the Massika cluster. One plot was not established due to its location in a flooded area in the northern Ekouk cluster.

In total, field teams measured 12,914 trees, representing 53 families. 72.5% of stems were identified to genus and 73.2% of these were identified to species (Table 1). The Massika cluster contained a significantly higher number of stems than the Ekouk cluster, but average height, DBH, plot basal area, and wood density did not differ significantly between the two clusters (Table 2).

Plot-level AGB ranged from 23.4-576.6 Mg ha^{-1} with an average AGB of 260.3 ± 115.2 Mg ha^{-1} across the landscape. There was no significant difference in average AGB between the two clusters (Table 2).

3.2 Landscape Estimate of Aboveground Biomass and Carbon Emissions

The mean canopy height according to the LiDAR first returns was significantly higher in the Ekouk cluster (32.3m; 95% CI = [29.8m, 34.9m]) compared to the Massika cluster (26.5m; 95% CI = [23.4m, 29.6m]). Overall, the mean canopy height across the landscape was 30.9m (95% CI = [28.7m, 33.1m]; Figure 2).

Most of the LiDAR metrics were highly correlated with each other. The mean height of the 75th percentile of first returns (H$_{75th}$) was most strongly correlated with AGB and was the only variable retained in the final regression model. The final model accounted for 67% of the variance in AGB (R^2 = 67.2%, F = 69.6, $p < 0.001$), with a prediction error of 7.97% (Figure 3).

Applying the model across the landscape, AGB ranged from 0-434.7 Mg ha^{-1} with an average AGB of 147.6 ± 61.3 Mg ha^{-1}. The AGB ranged from 0-434.7 Mg ha^{-1} across the Ekouk cluster with an average of 152.0 ± 64.6 Mg ha^{-1}. AGB ranged from 0-333.6 Mg ha^{-1} for the Massika cluster with an average of 133.0 ± 48.4 Mg ha^{-1} (Figure 4). The spatial model predicted 6.55 Tg C (95% CI = [6.53 Tg C, 6.57 Tg C]) in the Ekouk cluster and 2.14 Tg C (95% CI = [2.13 Tg C, 2.15 Tg C]) in the Massika cluster.

Total emissions from the complete development of both clusters would result in 39.23 Tg CO$_{2eq}$.

$$39.23 \, Tg \, CO_{2 \, eq} = (8.69 \, Tg \, C \, + \, 6.14 \, Tg \, C \, - \, 4.13 \, Tg \, C) \times \left(\frac{44 \, Tg \, CO_{2 \, eq}}{12 \, Tg \, C} \right)$$

To identify high carbon stock forest, we quantified all areas with AGB greater than 118 Mg ha^{-1}. 7.7% (6,430 ha) of the Ekouk cluster was identified as high carbon areas, totaling 17.1% (1.12 Tg C) of the carbon found in the cluster. Only 1.9% (598 ha) of the Massika cluster was identified as high carbon area, totaling 0.5% (0.01 Tg C) of the carbon in the cluster (Figure 5). By protecting areas that have AGB estimates greater than 118 Mg ha^{-1}, 9.6% of the total land area would be set aside between the two clusters, protecting approximately 1.13 Tg of carbon. Once these areas were buffered to protect them against edge effects, approximately 56.0% (3.67 Tg C) of the total carbon and 46.7% of the total area within the Ekouk cluster would be conserved. By contrast, only 6.9% (0.15 Tg C) of the carbon and 5.6% of the area in the Massika cluster would be conserved (Figure 6).

To achieve net zero emissions, 60.5% of the total area of the Ekouk and Massika cluster would need to be set aside.

$$0.02\ Tg\ CO_{2\ eq} = (3.09\ Tg\ C\ +\ 2.73\ Tg\ C - 1.63\ Tg\ C - 4.18\ Tg\ C) \times \left(\frac{44\ Tg\ CO_{2\ eq}}{12\ TG\ C}\right)$$

Due to its low AGB, all of the Massika cluster could be converted into palm oil while protecting a large portion (85%) of the Ekouk cluster to obtain net zero CO_2 emissions (Figure 7).

3.3 Faunal Surveys

Between April and October of 2015, 68 transects were walked at 36 sites (mean = 1.9 transects/site) for a total of 133 km of transects. Of the 68 transects, 53 (104 km) were located in the Ekouk cluster while 15 (29 km) were established in the Massika cluster. Field teams made observations of several species including forest elephants, great apes, red river hogs and duikers (Table 3).

Estimation of species densities was not possible for primate species, red river hogs, or duikers because of low numbers of nest and dung observations.

3.4 Abundance and Density of Forest Elephants

We estimated elephant dung densities and elephant abundances using dung of all age classes. Field teams recorded 240 dung piles (2.03 dung km^{-1}) in the Ekouk cluster and 44 dung piles (1.41 dung km^{-1}) in the Massika cluster, for a total of 284 observations. The observations included 11.3% fresh or recent dung, 43.3% old dung, 42.3% very old and 3.2% fossilized dung. No dung was observed on 32 transects (47.1% of the transects). For Distance analysis, we truncated 6% of the data, eliminating 15 observations from the Ekouk cluster and 3 from the Massika cluster.

Elephant dung density across the landscape was 422.2 dung km^{-2}, with an average of 466.8 dung km^{-2} in the Ekouk cluster and 305.2 dung km^{-2} in the Massika cluster. Using the most conservative dung decay and defecation rates, the elephant density across the landscape is 0.25 elephants km^{-2}, with 0.27 elephants km^{-2} in the Ekouk cluster and 0.18 elephants km^{-2} in the Massika cluster (Table 4). There are an estimated 227 elephants (95% CI: 146, 352) within the Ekouk cluster and 56 elephants (95% CI: 29, 111) within the Massika cluster, and approximately 283 elephants (95% CI: 193, 416) across both areas (Figure 8).

3.5 *Species Distribution Modeling*

In the development of the SDM model to predict elephant habitat across the landscape, we removed two predictor variables due to multicollinearity (Table S1). The final model included distance to villages, the coast, secondary roads, major waterways, and the degree of slope. The final model explained 40.47% of the deviance in the data (p<0.001). The probability of being suitable elephant habitat ranged from 0-100% across both the Ekouk and Massika clusters (Figure 9). The model was highly sensitive, accurately predicting the presence of elephant dung in 69 of the 72 observed segments (sensitivity = 95.83%; p<0.001). Approximately half of the Ekouk cluster and half of the Massika cluster were considered suitable forest elephant habitat. There is some overlap between areas considered suitable forest elephant habitat and areas set aside as HCS. However, the complete conversion of the Massika cluster would result in a loss of approximately 33% of the suitable forest elephant habitat (Figure 10).

3.6 *Comparison between Aboveground Biomass and Forest Elephant Density and Habitat*

Comparing the density of dung to AGB, there was a weak, but statistically significant relationship between AGB and forest elephant dung density (Dung Density = -0.0719 + (0.0020 x AGB) + ((-3.1970 x 10^{-6}) x AGB^2), $R^2 = 0.1144$, $F_{2, 397} = 26.76$, $p < 0.001$; Figure 11).

Comparing the probability of being suitable forest elephant habitat to AGB, we found there to be a weak, but statistically significant relationship (Probability = -0.0841 + (0.0021 x AGB) – ((5.3670 x 10^{-6}) x AGB^2), $R^2 = 0.0492$, $F_{12\ 397} = 11.33$, $p < 0.001$, Figure 12).

4. DISCUSSION

Protecting standing forests to mitigate climate change and preserve biodiversity, including forest elephants, are two of the principal conservation goals for Gabon and Central Africa. The spread of palm oil through the Central African tropics threatens both of these goals (Linder, 2013; Meijaard and Sheil, 2013). One proposed solution to mitigate the threat of palm oil agriculture on the ecosystem is to locate plantations in "degraded" or low carbon forest so that they have minimal impact on carbon stocks (Tegegne *et al.,* 2016). Here we evaluated whether locating oil palm plantations in low carbon forest would also conserve elephant habitat.

When planning for RSPO certification with the goal of net zero carbon emissions, we have shown that areas set aside to protect carbon stocks do not fully protect forest elephant habitat. In other words, planning for palm oil with the goal of reducing carbon emission will not conserve elephants, and vice versa.

Our case study focuses on the relationship between forest elephants and forest carbon, and may not represent the relationship between forest carbon and other wildlife species. Forest elephants are a wide-ranging species whose habitat preference may be broader than other species (Eggert *et al.,* 2014). With this in mind, more research is necessary to understand the relationship between high carbon areas and other wildlife species, including endangered species like great apes and game species like duikers and red river hogs. There is also little information regarding how Central African forest elephants interact with a landscape dominated by palm oil plantations. Forest elephants may be more protected from poachers around palm oil plantations or they may encounter humans more often leading to a rise in human-wildlife conflict.

The two approaches used in this study to understand the relationship between forest elephant habitat and carbon stocks – density of indirect observations and SDM – could be repeated for any species where enough observation data has been collected. Relying on a density of presence points after sampling the landscape is both time consuming and costly due to the need to sample across the entire study area. However, the KDE method can be used to show general locations where secretive/rare species were found. SDM, on the other hand, does not model rare species well, but for common species, it can be applied to a large area without sampling the entire location.

As palm oil continues to spread across the tropics, understanding how to reduce the loss of carbon stocks and threatened species habitat will become paramount. The government of Gabon, in this case, has chosen a seemingly appropriate location for a palm oil plantation. The Ekouk and Massika clusters both have low AGB compared to the Gabon national average of 307.8 Mg ha^{-1} and forest elephant densities across the study site are 56% lower compared to other location in Gabon that average 0.62 individuals km^{-2} (ANPN, 2016; Poulsen *et al.,* in prep.). The low AGB and densities of forest elephants in the Ekouk and Massika clusters make them attractive for palm oil conversion; but they may not be representative of every proposed palm oil concession site, highlighting the need to follow strict guidelines to protect carbon stocks and wildlife habitat. In the end, careful planning before plantation develop could save both time and money by reducing restoration efforts in cases of species extirpation as a result of plantation development (Budiharta *et al.,* 2014).

This is the first study of its kind to consider both detailed carbon analyses and predicted forest elephant habitat. A strong overlap between protected high carbon areas and forest elephant habitat would have been ideal. However, using forest elephants as a model, our analysis of the Ekouk and Massika clusters demonstrated a weak relationship between high carbon areas and forest elephant habitat. As palm oil spreads through Central Africa, careful land use planning will need to occur to protect both carbon stocks and wildlife habitat.

5. ACKNOWLEDGEMENTS

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7. TABLES AND FIGURES

Table 1: A table showing families representing the top 50% of stems identified within each cluster. The dominant genera (top 50% of stems) within each family are shown in parentheses. Asterisk (*) denotes that a genus made up 100% of the stems identified within that family.

Ekouk Cluster		Massika Cluster	
Euphorbiaceae *(Macaranga)*	14.1%	Olacaceae *(Coula, Diogoa)*	11.9%
Urticaceae *(Musanga*)*	13.1%	Caesalpiniaceae *(Augouardia, Dialium)*	8.4%
Burseraceae *(Aucoumea, Santiria)*	10.5%	Rubiaceae *(Psychotria, Pausinystalia)*	8.4%
Myristicaceae *(Coelocaryon, Staudtia)*	7.4%	Annonaceae *(Greenwayodendron)*	7.5%
Olacaceae *(Coula, Diogoa)*	7.3%	Euphorbiaceae *(Klaineanthus, Macaranga, Plagiostyles)*	7.4%
		Ebenaceae *(Diospyros*)*	7.0%

Table 2: A table showing the forest characteristics for the entire OLAM Landscape and each cluster. Mean values with [95% confidence intervals] are shown. Student t-tests were used to test for a significant difference between the Ekouk and Massika clusters.

Metric of Forest Structure	Landscape (N = 36)	Ekouk (N = 27)	Massika (N = 9)	*p*-Value
AGB(Mg ha^{-1})	260.3 [222.7, 297.9]	244.8 [207.0, 282.5]	306.8 [209.4, 404.3]	0.27
Stem Count	348.3 [322.0, 374.5]	330.2 [300.9, 359.5]	402.4 [359.8, 445.1]	0.01
Height (m)	18.45 [17.3, 19.6]	18 [16.6, 19.4]	19.8 [18.6, 21.0]	0.06
DBH (cm)	25.07 [24.0, 26.1]	25.6 [24.3, 26.9]	23.49 [21.9, 25.1]	0.06
Plot Basal Area (m^2 ha^{-1})	25.7 [23.5, 27.9]	25.7 [23.3, 28.1]	25.71 [20.5, 30.9]	0.99
Wood Density (g cm^{-3})	0.579 [0.539, 0.620]	0.56 [0.511, 0.609]	0.637 [0.578, 0.696]	0.06

Table 3: A table showing the number of observations and encounter rate (observations km^{-1}) for each species or species group. Direct observations include vocalizations and visual sightings of animals. The Ekouk and Massika clusters were analyzed separately and combined (combined clusters = CC). We surveyed 104.0 km in the Ekouk cluster and 29.0 km in the Massika cluster for a total of 133.0 km.

Species	**Sign**	**CC No.**	**Ekouk No.**	**Massika No.**	**CC Encounter Rate**	**Ekouk Encounter Rate**	**Massika Encounter Rate**
Loxodonta cyclotis	Dung	284	240	44	2.13	2.31	1.52
	Trail	171	138	33	1.29	1.33	1.14
Great Apes (*G. gorilla, P. troglodytes*)	Dung	4	3	1	0.03	0.03	0.03
	Nest	89	89	0	0.67	0.86	0
Potamochoerus porcus	Dung	4	4	0	0.03	0.04	0
Cercopithecus nictitans	Direct Observation	5	3	2	0.04	0.03	0.07
Cercocebus torquatus	Direct Observation	1	1	0	0.01	0.01	0
Small duiker (*Cephalophus monticola*)	Dung	70	68	2	0.53	0.65	0.07
Medium duiker (*C. callipygus, C. nigrifrons C. ogilbyi, C. leucogaster,*)	Dung	47	42	5	0.35	0.4	0.17
Large duiker (*C. sylvicultor*)	Dung	10	10	0	0.08	0.1	0

Table 4: A table showing elephant dung and individual elephant density and abundance. Coefficient of variation (CV) values shown in parentheses in the first column.

Key Function - Uniform, Adjustment - Cosine, 0.75 Binning								
Elephant Density	**Dung disappearance (days)**	**Defecation rate (dung days^{-1})**	**Density (dung km^2)**	**Lower CI**	**Upper CI**	**Density (Ele. km^2)**	**Lower CI**	**Upper CI**
Ekouk (22.32%)	90.00	19.00	466.82	300.65	724.84	0.27	0.18	0.42
	45.50	18.07				0.57	0.37	0.88
	55.60	18.07				0.46	0.30	0.72
Massika (32.80%)	90.00	19.00	305.15	154.83	601.44	0.18	0.09	0.35
	45.50	18.07				0.37	0.19	0.73
	55.60	18.07				0.30	0.15	0.60
Clusters Combined (19.54%)	90.00	19.00	422.24	287.41	620.32	0.25	0.17	0.36
	45.50	18.07				0.51	0.35	0.75
	55.60	18.07				0.42	0.29	0.62
Elephant Abundance	**Dung disappearance (days)**	**Defecation rate (dung days^{-1})**	**Abundance (dung)**	**Lower CI**	**Upper CI**	**Abundance (Ele.)**	**Lower CI**	**Upper CI**
Ekouk (22.32%)	90	19	387708.41	249697.29	602000.20	226.73	146.02	352.05
	45.5	18.07				471.56	303.70	732.20
	55.6	18.07				385.90	248.53	599.19
Massika (32.80%)	90	19	96503.82	48963.19	190203.80	56.43	28.63	111.23
	45.5	18.07				117.37	59.55	231.34
	55.6	18.07				96.05	48.73	189.32
Clusters Combined (19.54%)	90	19	484212.23	329594.99	711362.20	283.17	192.75	416.00
	45.5	18.07				588.93	400.88	865.21
	55.6	18.07				481.95	328.06	708.04

Figure 1: The study site (114,676 ha) is located in the provinces of Estuaire and Moyen Ogooue and is comprised of the Ekouk Cluster (83,053 ha) and the Massika Cluster (32,623 ha). The survey effort is shown across the study area in terms of 1 ha forest inventory plots and 2 km wildlife transects.
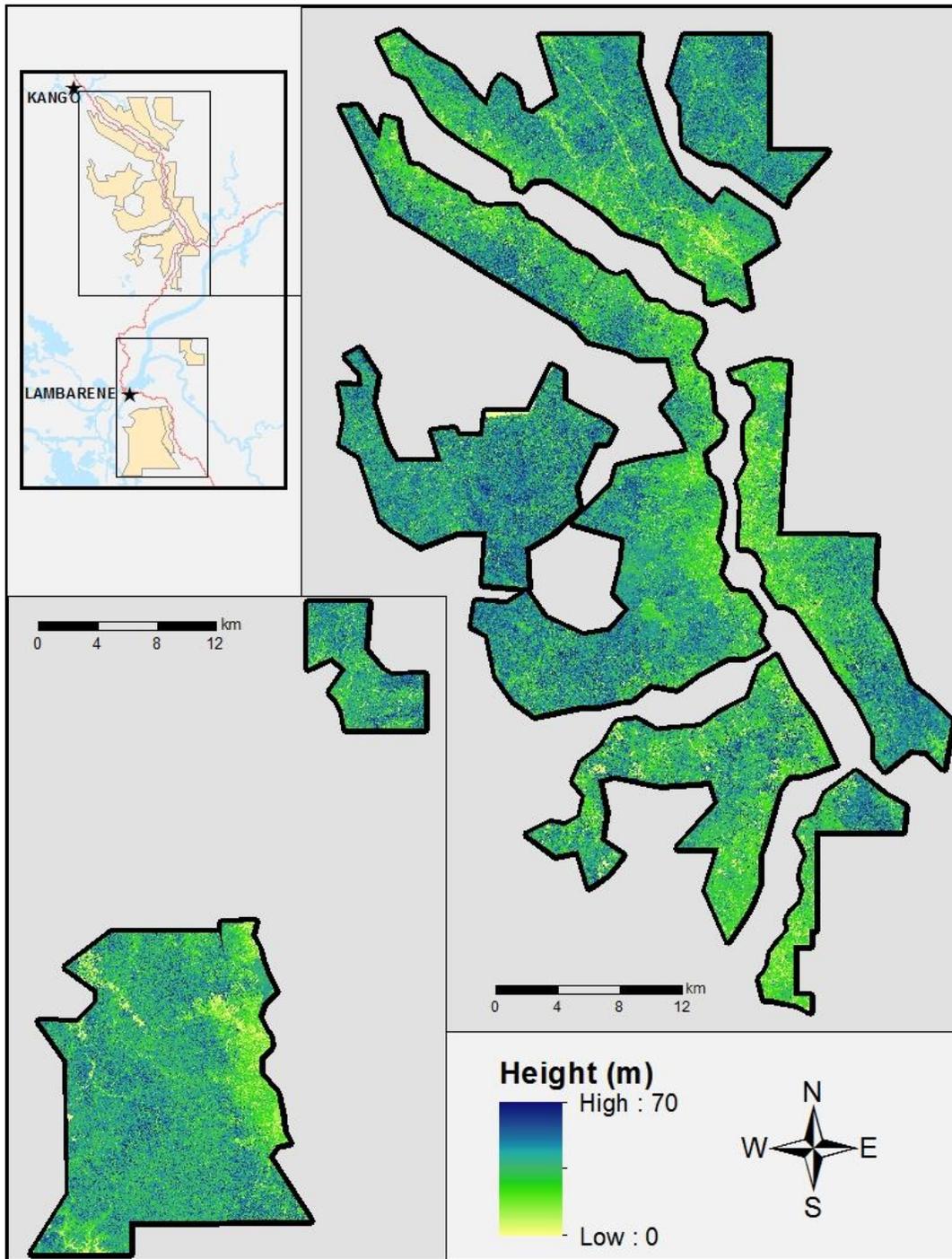
Figure 2: A map showing the canopy height (m) created from the LiDAR 1st returns. Student t-tests revealed there is no significant difference between the Ekouk and Massika clusters.
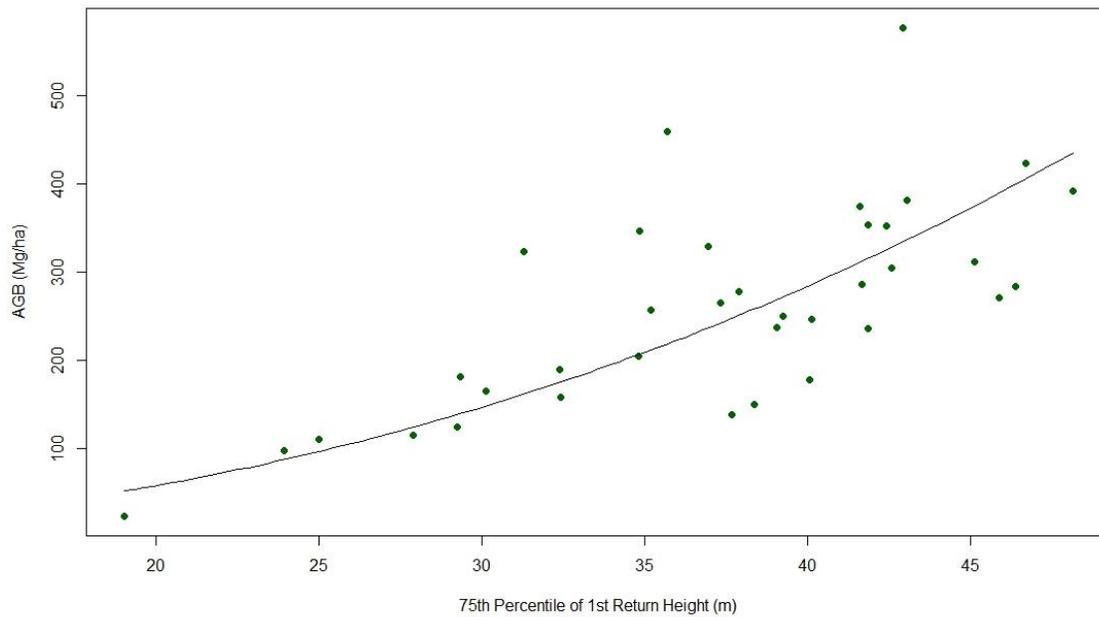
Figure 3: A plot showing the relationship between AGB (Mg ha^{-1}) measured in the field and the mean tree height. Mean tree height was estimated from the 75th percentile of the first return heights (m) from the remotely sensed LiDAR data (ln(AGB) = 0.0587 + (2.300 X ln(H$_{75th}$)).

Figure 4: Using remotely sensed LiDAR data and the results from the power law model, AGB (Mg ha⁻¹) was predicted across each cluster.

Figure 5: A map showing areas of high carbon. Areas in blue are estimated to have over 118 Mg C ha^{-1}. Nearly all of the high carbon areas are located in the Ekouk cluster.

Figure 6: Areas of high carbon were buffered 100 meters to protect against edge effects. Nearly all high carbon areas are located in the Ekouk cluster.

Figure 7: A map showing areas that should be set aside has high carbon stock areas (black lines). 100% conversion of the Massika cluster and 16.5% conversion on the Ekouk cluster will amount to net zero CO_2 loss.

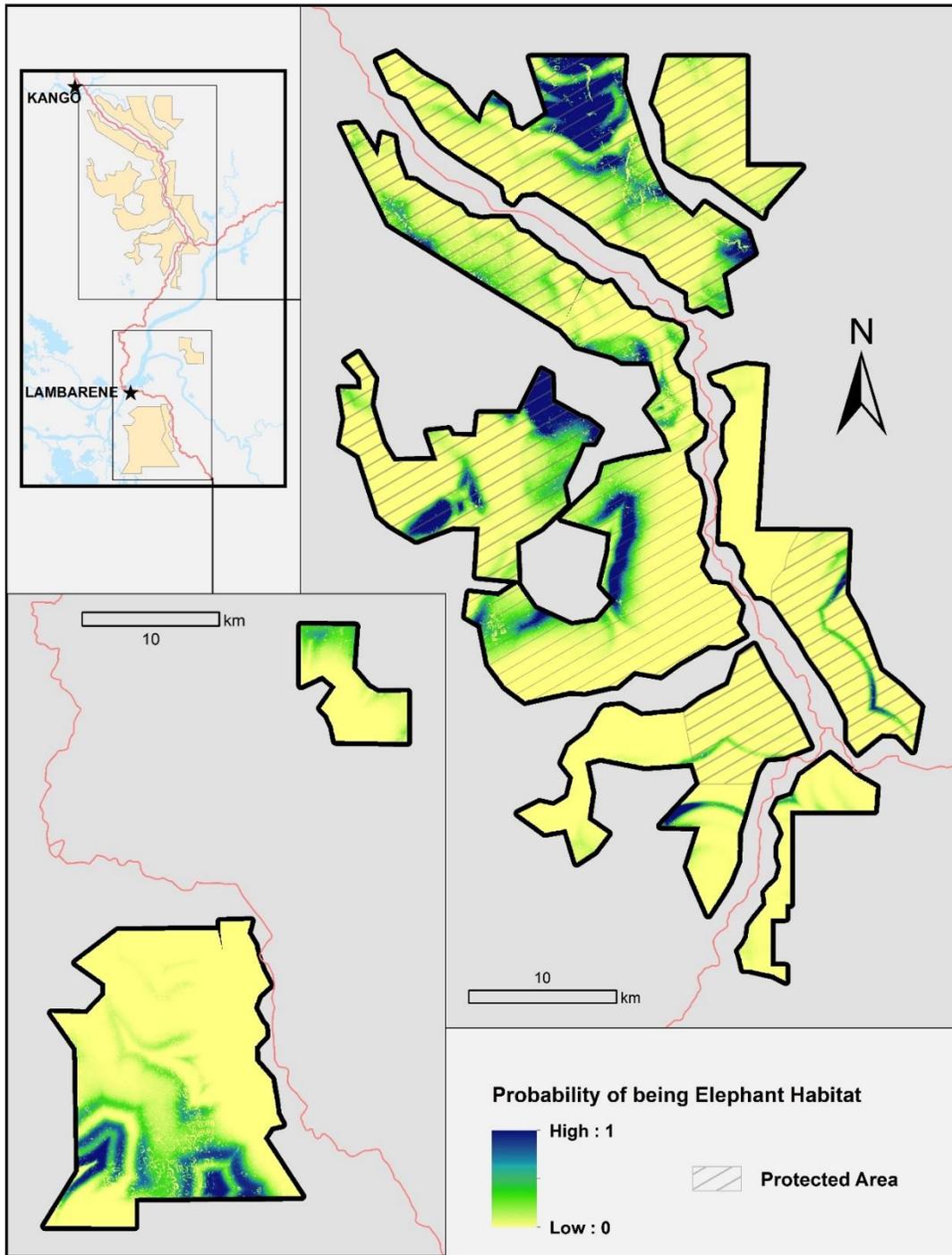*Figure 8: A map showing elephant dung density as a result of kernel density analysis using dung presence points.*

Figure 9: A map of the probability of an area being elephant habitat, as predicted by the SDM. Areas in blue have a higher probability of being elephant habitat versus areas in yellow.
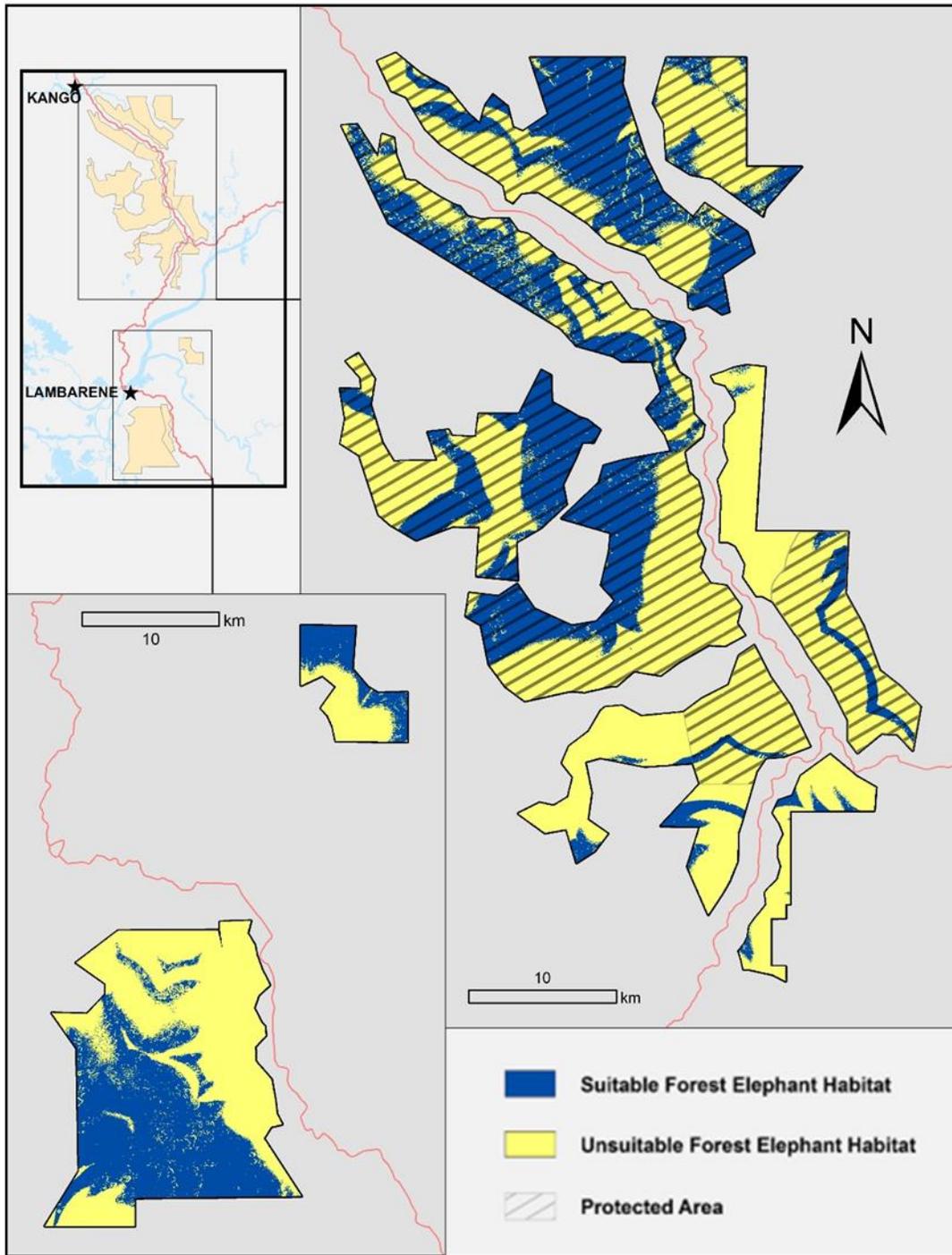
Figure 10: A map of the landscape classified as either suitable forest elephant habitat (blue) or unsuitable forest elephant habitat (yellow) based on the SDM.
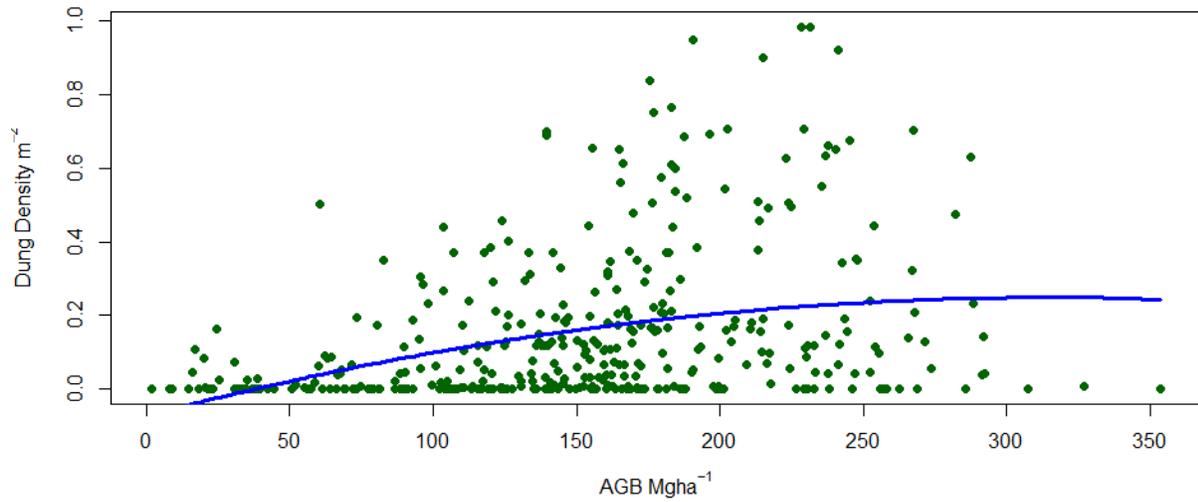
Figure 11: Using a polynomial regression model, there is a weak relationship between AGB and dung density across the landscape.
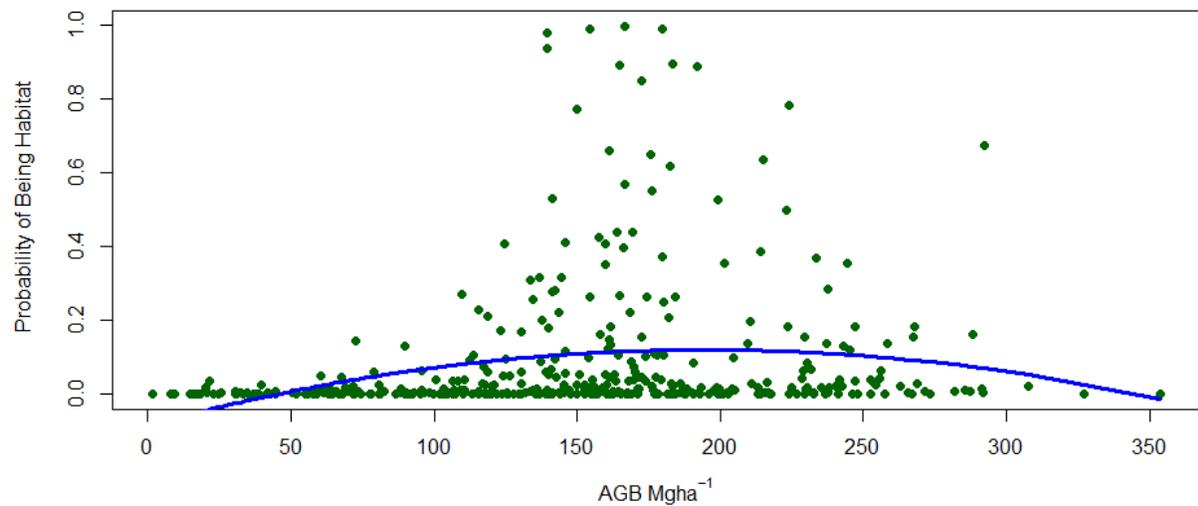

Figure 12: Using a polynomial regression model, there is a weak relationship between AGB and the probability of a location being suitable forest elephant habitat.

8. SUPPLEMENTARY

*Table S1: Explanatory variables. * Denotes variables used in the GAM modeling process.*

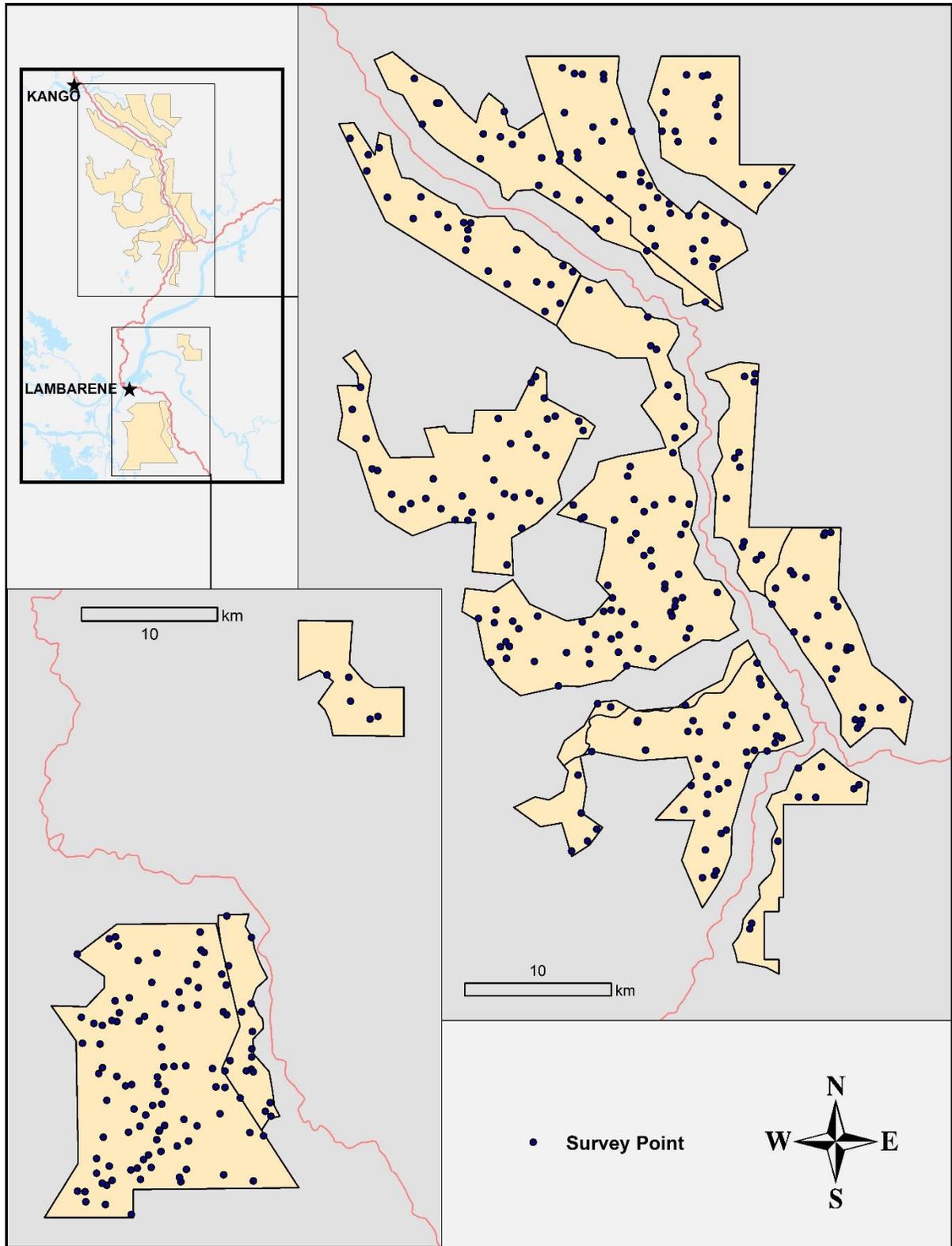| Variables	Description
Distance to Protected Areas*	Euclidean distance to protected areas (national parks and the presidential reserve)
Distance to Coast*	Distance to the Atlantic Ocean.
Distance to Nearest City*	Euclidean distance to nearest city. This dataset was created by the World Resource Institute for the Interactive Forest Atlas of Gabon. The source data were provided by the Forest and Environment Project (PFE - 1999/2000).
Distance to Nearest Village*	Euclidean distance to nearest village. This GIS layer was obtained by grouping multi-file by the World Resources Institute as part of the pilot version of the Atlas Interactive Forestry of Gabon. Source data come from the PFE (1999 /2000),
Distance to Nearest Major Road*	Euclidean distance to major roads. This theme includes all public roads in Gabon. This is the result of the work of PFE (1999/2000) and the National Institute of Cartography (INC). The last update of this layer as of September 2013.
Distance to Nearest Secondary Roads*	Euclidean distance to secondary roads. This theme includes logging, abandoned and other secondary roads. This is the result of the work of PFE (1999/2000) and the INC. The last update of this layer as of September 2013.
Distance to All Roads	Euclidean distance to all roads mentioned above.
Distance to Major Waterways*	Euclidean distance to major rivers and Gabon surface water bodies. This GIS layer is the result of the work of PFE (1999/2000) and the INC. The last update of this layer was in 2003.
Distance to Medium Waterways*	Euclidean distance to "medium" rivers. Created from 30meter DEM of Gabon. Hydrological layer thresholded so that pixels with pour point values greater than 10,000 and less than 60,000,000 become corresponding water features.
Distance to All Waterways	Euclidean distance to all rivers. Created from 30meter DEM of Gabon. Hydrological layer classified so that pixels with values greater than 10,000 become corresponding water features.
Elevation*	DEM of country created from SRTM 1 Arc Second. Elevation ranges from 0-1072m.
Slope*	Slope calculated from SRTM 1 Arc Second DEM tiles.

Figure S1: A map showing the 400 random points generated across the Ekouk and Massika clusters.