# Landscape Characteristics Influence Ranging Behavior of Asian Elephants at the Human-wildlands Interface in Myanmar

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**Research**

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# Abstract

**Context** Asian elephant numbers are declining across much of their range, driven largely by serious threats from land use change resulting in habitat loss and fragmentation. Myanmar, holding critical range for the species, is undergoing major developments due to recent sociopolitical changes. To effectively manage and conserve the remaining populations of endangered elephants in the country, it is crucial to understand their ranging behavior.

**Objectives** Our objectives were to (1) quantify dry season range sizes of elephants in Myanmar and assess how they vary with different configurations of agriculture and natural vegetation; and (2) evaluate how percentage of agriculture within dry core range of elephants relates to their daily distance travelled.

**Methods** We estimated dry season, wet season, and annual range sizes with autocorrelated kernel density estimator (AKDE) using a continuous-time movement modeling (ctmm) framework and reported the 95% and 50% AKDE and 95% Minimum Convex Polygon (MCP) range sizes. In a multiple regression framework, we developed candidate model sets to explain the variation in AKDE range sizes during the better sampled dry season when human-elephant interactions are the most likely to occur.

**Results** Elephant dry season ranges were highly variable averaging 792 $km^2$ and 184.2 $km^2$ for the 95% and 50% AKDE home ranges, respectively. We found both the shape and spatial configuration of agriculture and natural vegetation patches within an individual elephant's home range play a significant role in determining the size of its range. We also found that elephants are moving more (larger energy expenditure) in ranges with higher percentages of agricultural area.

**Conclusion** Our results provide baseline information for advancing future land use planning that takes into account space-use requirements for elephants. Failing to do so may seriously further endangered declining elephant populations in Myanmar and across the species' range.


# Introduction

The ability to understand how range size and movement patterns of a species vary in changing landscape is important for informing decision processes and landscape planning efforts by resource managers and conservation agencies (Morato et al. 2016, 2018; Wadey et al. 2018). Information on space requirements across different levels of human presence on a landscape can guide planning efforts and ensure success of objectives. The advent of GPS technology in wildlife telemetry has revolutionized how movement data are collected in the field of wildlife science (Wall et al. 2014; Kays et al. 2015). The ability to collect large volumes of location data with high temporal resolution allows robust inference on spatial requirements, including home range size, range shifts by season, and movement patterns within the home range. When paired with a powerful open-source technology, such as Google Earth Engine, understanding of the spatial context of the movement and space use patterns can be determined with relative ease. Such information allows key conservation related questions to be addressed, advancing

ecological knowledge of a species, and serving to answer applied questions (Gorelick et al. 2017; Seidel et al. 2018; Wittemyer et al. 2019).

To understand the drivers of an animal's movements, it is critical to appropriately understand the landscape context influencing its movement decisions (Nathan et al. 2008). Traditionally, ecologists have used software, such as FRAGSTATS, to quantify landscape metrics (Lamine et al. 2018) and address related ecological questions of interest (Midha and Mathur 2010). However, new analytical approaches are providing ecologists with more flexibility and unified workflow within one programming environment such as R (Hesselbarth et al. 2019). Easy extraction and quantification of landscape conditions using such platforms allow ecologists to carry out further analysis, such as data visualization, exploratory factor analysis, and generalized linear regression, to make inference on the ecological influence of landscape variables (Seidel et al. 2018). Coupling such information with data on animal space use can allow deeper insight to the landscape – space-use relationship.

The endangered Asian elephant (*Elephas maximus*), is particularly susceptible to habitat loss being the largest terrestrial mammal with large and heterogeneous habitat requirements (Owen-Smith 1989; Sukumar 1989; Fernando et al. 2008). The species is facing serious anthropogenic pressure across its geographic range (Santiapillai and Jackson 1990; Leimgruber et al. 2003; Choudhury et al. 2008; Calabrese et al. 2017). Agricultural expansion driving habitat fragmentation and loss, and resulting in significant human-elephant conflict and often the killings of people and elephants represents a major threat to remaining elephant populations. This is exacerbated by the persistent threat of poaching to the survival of remaining elephant populations across Asia (Leimgruber et al. 2003; Calabrese et al. 2017; Sampson et al. 2018).

Myanmar, home to approximately 1,400 wild elephants (Leimgruber and Wemmer 2004), has the largest amount of remaining wildlands among the species range countries (37.86 %) although the landscape is changing rapidly (Leimgruber et al. 2003, 2011). The status of Myanmar's elephants is unclear, but likely elephants are declining as they continue to face threats in the wild (Leimgruber et al. 2011; Songer et al. 2016). Recent evidence of increased poaching is a serious concern (Sampson et al. 2018). At the same time, range loss, driven by rapid development across the country due to recent changes in the political system and an increased development focus (Prescott et al. 2017), is thought to be the primary driver of elephant decline in the country. One study suggested that the geographic distribution of elephants in Myanmar declined by 5% (~ 15,000 $km^2$) between 1992 and 2006 (Songer et al. 2016). Even within a proposed national park in Myanmar, forest cover is declining (Connette et al. 2017). There are only a few studies that have assessed the space use of wild Asian elephants (Fernando et al. 2008; Kumar et al. 2010; Alfred et al. 2012; Moßbrucker et al. 2016), and no empirical data on ranging behavior of wild elephants in Myanmar can be found in the literature to our knowledge. Therefore, it is crucial to obtain and document the information relating space use and ranging behavior of elephants in the country.

Developing tools for assessing elephant space use and ranging requirements becomes even more critical with continued habitat loss. As human populations continue to increase, human encroachment into the

remaining “wildlands” within the elephant’s range countries is likely to accelerate. This encroachment will inevitably lead to increase in human-elephant encounters and conflict. Additionally, increased fragmentation due to habitat loss could result in increased range size as elephants are forced to move further in order to meet the resource requirements (Fernando et al. 2005; Alfred et al. 2012). Particularly in the dry season when configuration of resources varies across the landscape, elephants are more likely to change their ranging pattern in response to fragmentation (Sukumar 1989; Campos-Arceiz et al. 2008).

We looked at the relationship between animal space use and landscape context, by deriving metrics describing shape and configuration of land cover types within individual ranges. Our two main objectives of this study were to (1) quantify dry season range sizes in Myanmar and assess how ranging behavior during the dry season varies based on different configurations of available agriculture and natural vegetation (including testing for range size thresholds relative to percentage of agriculture); and (2) evaluate how percentage of agriculture within dry core range of elephants relates to their daily distance traveled. In addition, we examined wet season ranging behavior where data allowed.

## Methods

# Study Areas

Our study was conducted in three areas of conservation interest in central, western, and southern Myanmar– site 1(Latitude: 17.1013–18.1960, Longitude: 95.7043–96.4787), site 2 (Latitude: 16.0554–17.0842, Longitude: 94.1860–94.6838), and site 3 (Latitude: 10.7141–12.0981, Longitude: 98.3356–99.4626) (Fig. 1). Site 1 is located in the central part of Myanmar in the foothills of Bago Yoma mountain ranges. Historical unsustainable teak extraction in this site created a highly disturbed forest mosaic that is increasingly being invaded by other human land uses, including the construction of hydroelectric reservoirs, settlements, as well as commercial teak, sugarcane, rice, and rubber plantations. Site 2 is a mountainous area along the west coast of the Ayeyarwaddy delta region that stretches from north to south creating an elongated forest with hard boundaries on east and west. Rice plantations dominate the matrix between forest patches in this site, where rubber and peppercorn agricultural use is also prevalent. Site 3 is part of the larger Dawna Tanintharyi Landscape which extends from mountain ridges along the border with Thailand to the coastal plain. Land use at site 3 is primarily composed of oil palm and betel nut plantations, surrounded by lowland deciduous forests. Threats of human encroachment, road development, and agricultural expansion into the remaining forest are rising in the area.

The study areas are strongly seasonal, with rainfall records demonstrating the extended dry season occurs between early December and late March, and the wet season between early June and mid-September (Biswas et al. 2015). During the dry season, human-elephant conflicts (HECs) peak in relation to the harvest of rice, sugarcane, and other agricultural products (Sukumar 2003). Rainfall is significantly higher at site 3, resulting in markedly different forest composition. Forests at site 3 are predominantly lowland evergreen forests, while at site 1 and 2, they are mostly mixed deciduous forests with strong seasonal leaf fall patterns.

# Elephant Capture for GPS collaring

All capture and animal sedation were performed by Myanmar Timber Enterprise (MTE) veterinarians. MTE is the Myanmar government agency responsible for the management of logging elephants and their staff have extensive experience in veterinary care of captive and wild Asian elephants, including sedation. All capture and handling procedures followed or exceeded the guidelines provided by the American Society of Mammalogists (Sikes 2016). Elephants were immobilized using Etrophine and Xylaxine for sedation and Naltrexone for reversal. The immobilization and collaring process took approximately 30 minutes per individual and was carried out early in the morning or late in the afternoon when air temperature was lower (< 35° C). Due to high collar failure and poaching soon after collar deployments (Sampson et al. 2018), telemetry datasets were often patchy and covered relatively short periods. Consequently, we only included individuals with: 1) > 60 days of tracking data and/or 2) that had a well-established home range. To assess whether animals established home ranges during the tracking periods, we used methods described by (Calabrese and Fleming 2016) in their continuous-time movement modeling package (ctmm) in R. If the semi-variogram function for the relocation data of an elephant approached an asymptote, we classified it as an established range during the period of interest (Calabrese and Fleming 2016).

For dry season range analysis, we included eight individuals from site 1 (4 females: 4 males), six from the site 2 (1 female: 5 males), and eight from site 3 (2 females: 6 males) – totaling 22 different individuals. We performed data analysis on data collected from December 2016 through March 2020. Therefore, our analysis covers four dry seasons. Since there are four individuals whose tracking periods cover two dry seasons, our sample size for the dry season analysis includes 26 different seasonal ranges.

For the wet season ranges estimation, we utilized data from five individuals from site 1 (1 female: 4 males), three from the site 2 (3 males), and two from site 3 (2 males). There were two individuals who had data spanning two wet seasons, bringing the sample size of the wet season analysis to 12 estimated ranges.

For annual home range estimation, we only included individuals with > 365 days tracked, which amounted to 8 individuals: five individuals from site 1 (1 female: 4 males), one from the site 2 (a male), and two from site 3 (2 males).

# Range Estimation

We employed ctmm framework (Calabrese and Fleming 2016) to estimate seasonal (dry and wet) and annual home range sizes among individuals. We compared the fit to our data of independent and identically distributed (IID), Ornstein-Uhlenbeck (OU), and Ornstein-Uhlenbeck Foraging (OUF) movement models using maximum likelihood and ranked the individual performance using Akaike Information Criterion (AICc). We picked the top-ranking model according to AIC scores, and applied it to fit the autocorrelated density estimator (AKDE) function to estimate range size. We presented 95% and 50%

AKDE percentile level ranges for all individuals. We also assumed 50% AKDE level as core areas within the respective ranges where animals spent 50 percent of their time. We assessed both 95 % and 50 % AKDE percentile so that this study is readily comparable to other studies. We also calculated 95 percentile minimum convex polygon (MCP) for comparison with other studies using the same metric.

# Predictor variables and candidate models

To assess which landscape conditions were related to dry season range size, we applied gamma regression models with a log-link function to identify correlates of range size. First, we developed land cover maps for our study areas by classifying Landsat imageries (Chan et al. unpublished data). We used the 'landscapemetrics' package in R to derive different measures for characterizing landscape metrics from our land cover map (Hesselbarth et al. 2019). To describe the landscape of each individual range, we calculated several different shape, area, edge, and aggregation metrics for water, agriculture, and natural vegetation classes (Table 1). In addition, we quantified landscape-level metrics, including Shannon's diversity index, relative patch richness, and relative patch density (Table 1). We computed 48 landscape metrics in total.

We relied on exploratory factor analysis with oblique minimal rotation of principal factor axes to reduce the data dimensionality to simplify these 48 metrics for our regression analysis. This approach relaxes the assumption of normality (Costello and Osborne 2005) and allowed us to identify the variables that best characterized variation in our landscapes (Table 1). Specifically, we included highest positive and negative loading variables from the first five principle factor axes to reduce the metrics to the primary explanatory variables while explaining sufficient variance in the data. Afterwards, we compared single variable models among metrics belonging to the same land cover class. We kept the variables if the AIC corrected for small sample size (AICc) score was within 8 of the top model and did not consider variables that did not met the criteria in our candidate model set. This allowed us to eliminate variables with relatively low explanatory power. We also assessed the Spearman's correlation metrics between all the variables before including them in the final candidate model sets. We then developed different biologically meaningful combinations of agriculture and natural vegetation in the model set with the retained variables for both the 95% and 50% AKDE level. We included a model with a quadratic term for percentage of agriculture to determine whether we can assess the threshold relationship with it and range size. We used gamma regression model, a type of generalized linear model, to develop both candidate model sets based on the assumption that our response variable, range sizes, can only be non-zero positive number.

We also developed a candidate model set to assess the correlation between landscape metrics and average daily distance moved by the elephants. For this particular candidate model set, we tested several hypotheses using the most informative variables from the 50% AKDE dry season analysis. We tested whether sex, region, and/or two agriculture metrics (percentage of agriculture presence and perimeter-area ratio of agriculture patches within the range) influenced average daily distance moved by elephants

by fitting gamma regression model as described above. We set female and study site 2 as a reference category for sex and region categorical predictor variables, respectively, in the model.

We used AICc to rank models in the candidate model set (Burnham and Anderson 2002). We selected our top model (the lowest AICc) as the best model. To account for variation in range sizes driven by sampling differences, we included the number of days tracked as an additional variable in the top model. We retained the number of days tracked variable if it was included in a model within 2 AICc scores of the top model. Since some of the individuals contribute more than one range estimate in the dataset, we tried to account for individual variation by adding random intercepts in the top model; however, the model with the random intercept did not converge due to low sample size. All variables were standardized to a mean of 0 and a standard deviation of 1 before fitting the generalized linear regression model. All analyses were conducted in R version 3.6.3 using 'ggplot2', 'dplyr', 'ctmm', 'landscapemetrics', and 'AICcmodavg' (Wickham 2011; Marc J. Mazerolle 2015; Wickham et al. 2018; Hesselbarth et al. 2019; Fleming and Calabrese 2020; R Core Team 2020).

# Results

Home range size estimates varied across seasons and individuals. We did not perform a statistical test to evaluate the sex specific differences in range size among the study region due to limited sample size. However, the large amount of variation observed in range size indicated differences within our sample were not likely (average and standard deviation of female 50% AKDE = 153 $km^2$ +/- 221 $km^2$; average and standard deviation of male 50% range: 196 $km^2$ +/- 199 $km^2$). Elephant dry season ranges were highly variable averaging 792 $km^2$ (+/- 867.6 $km^2$; range from 38.4 $km^2$ to 3,166.4 $km^2$) for the 95% AKDE ranges while the 50% AKDE range sizes averaging 184.2 $km^2$ (+/- 201.5 $km^2$; range: 7.4 $km^2$ to 728.5 $km^2$). Despite more limited sample sizes ($n_{wet}$ = 12, $n_{annual}$ = 8), analysis of wet season range indicated the average 95% AKDE ranges was 1,520 $km^2$ (range: 43.5–5,362.2 $km^2$), and the average AKDE 50% ranges was 356.1 $km^2$ (range: 12.8–1,277.5 $km^2$). Considering only full annual ranges, the average range covered 1,093.1 $km^2$ (range: 89.6–3,057.4 $km^2$) and 252.9 $km^2$ (range: 20.3–777.2 $km^2$) for 95 % and 50% AKDE home ranges respectively.

The variation in 95% AKDE level dry season ranges was best explained by metrics characterizing agricultural land use rather than those of natural areas; whereas, metrics describing landscape configuration of natural vegetation classes explained the difference in range sizes better for 50% AKDE level (core range area) (Table 1). The top models contained four statistically significant variables with three agriculture and one natural vegetation metrics in the top model for potential range and vice versa for that of core range area (Figs. 2 and 3).

The top model for 95% range included significant coefficient estimates for percentage of agriculture on the landscape, fractal dimension mean and edge density of agriculture, and the coefficient of variation of patch area for natural vegetation (Fig. 2). In general, elephants tend to require larger 95% range when the

shape of agriculture patches are irregular (higher mean fractal dimension) and agriculture land use percentage on a landscape increased. On the other hand, more patchy agriculture on a landscape (higher edge density) corresponded to smaller 95 % range (Fig. 1). On average, one unit increase in the metric describing variation in natural vegetation patches (1 standard deviation from the mean) corresponded to 3.4 $km^2$ increase in potential range size while holding the rest of the variables in the model at their mean value (Fig. 4).

The top model for 50% AKDE of the estimated dry season range included significant coefficient estimates for mean perimeter to area ratio and mean number of disjunct areas of natural vegetation and landscape shape index for agriculture (Fig. 3). Smaller core range areas corresponded to more complex natural vegetation patches (increase in perimeter-area ratio). On the other hand, larger core range sizes corresponded with less compact patches of agriculture (i.e. higher landscape shape index) and larger average number of disjunct core natural vegetation patches within the ranges (Fig. 5). On average, an increase of 14.6 landscape shape index score for agriculture corresponded to a 2.9 $km^2$ increase in core range area.

# Daily Travel Distance

Mean average daily distance traveled by the elephants in the dry season was 3.9 km (range: 1.3–7.3 km). The mean distance of average daily distance moved by males was 3.8 km (+/- 1.6; n = 19) and that of females was 4.1 km (+/- 1.6; n = 7). According to our top model, the average daily distance moved by the elephants was 3.8 km at 13.9 percent agriculture within their home range (Table 4). Only the variable percentage of agriculture on a landscape (pland_ag) was included in our top model of average daily distance moved by elephants in our study. An approximate increase of 15 percent in agriculture on the landscape resulted in an increase of 1.2 km in the daily distance traveled by the elephants. Study sites and sex of the individual were not included in the top model in our sample (Table 4).

## Discussion

Information on spatial requirements of Asian elephants across different degrees of human modification is critical to identify where and under what circumstances elephants can be sustained on human dominated landscapes outside protected areas (Goswami et al. 2014). Due to the reported high variation in home range sizes and ranging patterns, local information on the Asian elephant ranging behavior in countries with little to no prior knowledge on the subject such as Myanmar is invaluable (Leimgruber et al. 2003; Fernando et al. 2008). This study provides the first estimates of wild Asian elephant ranges based on empirical data in Myanmar. Dry season 95% AKDE range sizes ranged from 38.4 $km^2$ to 3,166.4 $km^2$ in Myanmar which capture both ends of the spectrum of estimated ranges for Asian elephants reported in the literature – estimated home range sizes were between 51.2–179.2 $km^2$ in Sri Lanka, 122 – 114 $km^2$ in Malaysia, and 105–320 $km^2$ in India (Sukumar 1989; Fernando et al. 2008; Kumar et al. 2010); whereas, larger home range sizes were estimated in Cambodia (ranges from 275–

1,352 $km^2$) (Moßbrucker et al. 2016). The huge differences in the reported home range sizes could partially be accounted for by differences in the estimation method used. Future research should focus on comparing the home range sizes across the range countries using a standardized methodology for home range estimation to better understand the impact of land use on ranging behavior of elephants by removing a source of variation (differences in estimation methods) in the data.

We also explored why our average wet season estimate was larger than that for the annual range. To account for small sample size and widely dispersed relocation points due to irregular reporting during the wet season, our AKDE analysis yielded larger range sizes for wet season than annual ranges, despite the annual range estimates including all data used to estimate the wet season range (in addition to data from the dry season). To better understand this methodological artifact, we calculated 95% minimum convex polygon and found annual ranges were larger than wet season ranges (Table 5). As we suspected, the AKDE result was likely a result of the small sample size and temporally dispersed relocation points in the dataset (Fleming and Calabrese 2017).

One of the study objectives was to identify important landscape metrics in explaining variation in both 95 % and 50% AKDE ranges of Asian elephant during the dry season in Myanmar. It is inevitable that the species will face increasing fragmentation and habitat loss due to agricultural expansion and urbanization across the range countries (Leimgruber et al. 2003; Sodhi et al. 2004; Songer et al. 2016). It is also evident in the literature that level of human footprint on a landscape can affect movement of animals (Tucker et al. 2018). Therefore, it is crucial to quantify the structure and magnitude of fragmentation within the species' core range as a first step in any science-based management and conservation program. Previous research indicated that Asian elephants benefit from a mixture of natural vegetation and agriculture on a landscape (Fernando and Leimgruber 2011; Songer et al. 2016; Calabrese et al. 2017). We identified percentage of agriculture within an elephant's range, mean fractal dimension, and edge density of agriculture as the variables of importance in quantifying the level of fragmentation within an individual's potential range (i.e., 95% AKDE range). Within the elephant's core range (i.e., 50% AKDE range), we showed that landscape shape index for agriculture is the most important variable in explaining the variation in range sizes. We did not detect a relationship between range size thresholds relative to percentage of agriculture (our top model did not include the quadratic variable allowing such inference); however, further investigation on a larger data set would be valuable to determine the nature of this relationship. Sampling across a broader gradient of human agricultural use could provide more specific inference on this relationship, though it may be difficult to determine such thresholds if it is a gradual process and the number of elephants living near this theoretical threshold are small.

Average daily distance traveled was positively correlated with percent agriculture land use available within the core ranges in our analysis. This result is in agreement with the existing literature on Asian elephant's movement behavior in fragmented landscape, where elephants in more fragmented habitat are likely to move further (increased energy expenditure) to meet their survival and fitness requirements (Fernando et al. 2005; Campos-Arceiz et al. 2008; Alfred et al. 2012). It could also be the case that poaching risks are higher for those individuals within these more fragmented landscapes with higher

agriculture land use (Sukumar 1990; Webber et al. 2011). Increased movement could be a strategy whereby elephants reduce the inherent risk of being in close proximity to humans.

Asian elephant range sizes are thought to be strongly determined by availability of water on a given landscape (Sukumar 1989; Fernando et al. 2008); however, the variables capturing water land cover class were not included in top models of either potential range or core range sizes of elephants in our analysis for the dry season. This may indicate that water is not a limiting factor within these landscapes, possibly because elephants have already adjusted their range to meet their water requirement for the dry season or because water is relatively widely available. Alternatively, it is possible that land cover map used in this study did not adequately capture all aspects of water availability on the landscape, or that the grain of our satellite imageries used to produce our land cover maps (30 x 30 meters) was coarse to capture the seasonal variation of water sources within our study sites.

Elephants continue to face habitat loss and fragmentation across their range due to development (Leimgruber et al. 2003; Calabrese et al. 2017). This will in turn increase human-elephant encounters (Fernando et al. 2005). Although there are several ways to mitigate human-elephant conflicts particularly at the agricultural wildland interface, such as electric fencing, bee fencing, and chili fencing, it is important to identify if we are moving the problem elsewhere or the method is really effective (Barua et al. 2013; Shaffer et al. 2019). When deploying temporary or permanent fencing on a landscape, we are fragmenting the landscape, which can drive behavioral responses from the elephants. For instance, increased fragmentation in the study system is related to larger ranges. Thus, mitigation approaches could cause the elephants to move more broadly, potentially spreading conflict areas across a broader area. Our study provides a useful model to predict the degree to which ranging behavior of elephant could change based on changes in fragmentation on a landscape (e.g., an increase of 14.6 landscape shape index score for agriculture corresponded to a 2.9 $km^2$ increase in core range area on average). Elephants may be able to persist in these heterogeneous agriculture-natural-vegetation landscape mosaics for the long term if human-elephant conflicts can be managed appropriately by targeting actions that keep human and elephant casualties low and reduce economic impacts on local farmers. To reach this goal, it is important to pay attention to changes in elephant space use in relation to land use development and human-elephant conflict mitigation actions to help ensure ecologically sustainable policy and decisions by mangers and conservationists. It is also important to ensure the remaining wildlands for elephants are protected, which will provide refuge habitat and reduce the overall area use by elephants – range use increased with less natural area (Fig. 5).

# Conclusion

This study provides foundational information on the movement ecology and spatial behavior of Asian elephant in Myanmar. Although Myanmar has lower elephant number than countries such as Sri Lanka and India, it has large tracts of suitable habitat for Asian elephants, making it a key range country for the species (Leimgruber et al. 2003). Determining habitat requirements through studies of habitat selection and space use, can serve the country by providing managers and policy makers with concrete

information on habitat requirements of this endangered species. This study provides such baseline information, while also providing insight to how landscape structure influences elephant space use. It also highlights the importance of assessing elephant use of areas outside of protected areas, which have been traditionally overlooked. Since it was predicted that 41.8 % of the 256,518 km2 of the available habitat for Asian elephants will be lost by the end of century (Kanagaraj et al. 2019), we could expect more fragmentation and land use changes within elephant's core ranges which could potentially lead to larger ranging behavior increasing both the number of and chances of human-elephant conflicts. It is time for us to apply science-based proactive management to save this species.

# Declarations

### Ethics approval and consent to participate

Protocols for all animal capture and handling followed national veterinary service policies and were reviewed and approved under IACUC from Smithsonian Institution (Approval Number: 17-30).

### Consent for publication

Not applicable

### Availability of data and materials

Data will be available on request but can not be released publicly due to the endangered status of Asian elephants.

### Competing Interests

We declare no competing interest among all co-authors.

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### Authors' Contributions

Chan, A.N. - study design, data collection and analysis, writing manuscript

Wittemyer, G. - study design, data analysis, and editing manuscript

McEvoy, J. - data collection and editing manuscript

Williams, A.C. - study design and editing manuscript

Cox, N. - study design and editing manuscript

Soe, P. - data collection and editing manuscript

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Shwe, N.M. - data collection and editing manuscript

Chit, A.M. - data collection

Oo, Z.M. - data collection

Leimgruber, P. - study design, data analysis, and editing manuscript

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# References

1. Alfred R, Ahmad AH, Payne J, et al. Home range and ranging behaviour of bornean elephant (elephas maximus borneensis) females. PLoS One. 2012. https://doi.org/10.1371/journal.pone.0031400.
2. Barua M, Bhagwat SA, Jadhav S. The hidden dimensions of human-wildlife conflict: Health impacts, opportunity and transaction costs. Biol Conserv. 2013;157:309–16. https://doi.org/10.1016/j.biocon.2012.07.014.
3. Biswas S, Vadrevu KP, Lwin ZM, et al. Factors controlling vegetation fires in protected and non-protected areas of Myanmar. PLoS One. 2015;10:1–18. https://doi.org/10.1371/journal.pone.0124346.
4. Burnham KP, Anderson DR. (2002) Model Selection and Multimodel Inference.
5. Calabrese A, Calabrese JM, Songer M, et al. Conservation status of Asian elephants: the influence of habitat and governance. Biodivers Conserv. 2017;26:2067–81. https://doi.org/10.1007/s10531-017-1345-5.
6. Calabrese J, Fleming C. (2016) ctmm: an r package for analyzing animal relocation data as a continuous-time stochastic process. Methods Ecol.
7. Campos-Arceiz A, Larrinaga AR, Weerasinghe UR, et al. Behavior rather than diet mediates seasonal differences in seed dispersal by Asian elephants. Ecology. 2008;89:2684–91. https://doi.org/10.1890/07-1573.1.

8. Choudhury A, Lahiri Choudhury DK, Desai A, et al (2008) Elephas maximus. The IUCN Red List of Threatened Species 2008. IUCN Red List Threat Species 2008 8235:16. https://doi.org/http://dx.doi.org/10.2305/IUCN.UK.2008.RLTS.T7140A12828813.en.
9. Connette GM, Oswald P, Thura MK, et al (2017) Rapid forest clearing in a Myanmar proposed national park threatens two newly discovered species of geckos (Gekkonidae: Cyrtodactylus). PLoS One 12:. https://doi.org/10.1371/journal.pone.0174432.
10. Costello AB, Osborne JW. Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. Pract Assessment Res Eval. 2005;10:173–8.
11. Fernando P, Leimgruber P. (2011) Asian Elephants and Seasonally Dry Forests. Ecol Conserv Seas Dry For Asia 151–163.
12. Fernando P, Wikramanayake E, Weerakoon D, et al. Perceptions and patterns of human-elephant conflict in old and new settlements in Sri Lanka: Insights for mitigation and management. Biodivers Conserv. 2005;14:2465–81. https://doi.org/10.1007/s10531-004-0216-z.
13. Fernando P, Wikrarnanayake ED, Janaka HK, et al. Ranging behavior of the Asian elephant in Sri Lanka. Mamm Biol. 2008;73:2–13. https://doi.org/10.1016/j.mambio.2007.07.007.
14. Fleming CH, Calabrese JM. A new kernel density estimator for accurate home-range and species-range area estimation. Methods Ecol Evol. 2017;8:571–9. https://doi.org/10.1111/2041-210X.12673.
15. Fleming CH, Calabrese JM. (2020) ctmm: Continuous-Time Movement Modeling.
16. Gorelick N, Hancher M, Dixon M, et al. Google Earth Engine Planetary-scale geospatial analysis for everyone. Remote Sens Environ. 2017. https://doi.org/10.1016j.rse.2017.06.031.
17. Goswami VR, Sridhara S, Medhi K, et al. Community-managed forests and wildlife-friendly agriculture play a subsidiary but not substitutive role to protected areas for the endangered Asian elephant. Biol Conserv. 2014;177:74–81. https://doi.org/10.1016/j.biocon.2014.06.013.
18. Hesselbarth MHK, Sciaini M, With KA, et al. landscapemetrics: an open-source R tool to calculate landscape metrics. Ecography. 2019. https://doi.org/10.1111/ecog.04617.
19. Kanagaraj R, Araujo MB, Barman R, et al. Predicting range shifts of Asian elephants under global change. Divers Distrib. 2019;25:822–38. https://doi.org/10.1111/ddi.12898.
20. Kays R, Crofoot MC, Jetz W, Wikelski M. (2015) on life and planet. Ecology 348:. https://doi.org/10.1126/science.aaa2478.
21. Kumar MA, Mudappa D, Raman TRS. Asian Elephant Elephas Maximus Habitat Use and Ranging in Fragmented Rainforest and Plantations in the Anamalai Hills, India. Trop Conserv Sci. 2010;3:143–58. https://doi.org/10.1177/194008291000300203.
22. Lamine S, Petropoulos GP, Singh SK, et al. Quantifying land use/land cover spatio-temporal landscape pattern dynamics from Hyperion using SVMs classifier and FRAGSTATS®. Geocarto Int. 2018. https://doi.org/10.1080/10106049.2017.1307460.
23. Leimgruber P, Gagnon JB, Wemmer C, et al. Fragmentation of Asia's remaining wildlands: Implications for Asian elephant conservation. Anim Conserv. 2003;6:347–59.

https://doi.org/10.1017/S1367943003003421.

24. Leimgruber P, Wemmer C. (2004) National Elephant Symposium and Workshop. Report to the USFWS and the Myanmar Forest Department.
25. Leimgruber P, Oo Z, Aung M, et al. Current status of Asian elephants in Myanmar. Gajah. 2011;35:76–86.
26. Marc J. Mazerolle. (2015) Package ‘ AICcmodavg.’ R Environ 1–141.
27. Midha N, Mathur PK. Assessment of forest fragmentation in the conservation priority Dudhwa landscape, India using FRAGSTATS computed class level metrics. J Indian Soc Remote Sens. 2010. https://doi.org/10.1007/s12524-010-0034-6.
28. Morato RG, Connette GM, Stabach JA, et al. Resource selection in an apex predator and variation in response to local landscape characteristics. Biol Conserv. 2018;228:233–40. https://doi.org/10.1016/j.biocon.2018.10.022.
29. Morato RG, Stabach JA, Fleming CH, et al. Space use and movement of a neotropical top predator: The endangered jaguar. PLoS One. 2016;11:1–17. https://doi.org/10.1371/journal.pone.0168176.
30. Moßbrucker AM, Fleming CH, Imron MA, et al. AKDEC home range size and habitat selection of Sumatran elephants. Wildl Res. 2016;43:566–75. https://doi.org/10.1071/WR16069.
31. Nathan R, Getz WM, Revilla E, et al. A movement ecology paradigm for unifying organismal movement research. Proc Natl Acad Sci. 2008. https://doi.org/10.1073/pnas.0800375105.
32. Owen-Smith N. (1989) Megaherbivores: the influence of very large body size on Ecology by R N Owen-Smith, Cambridge studies in ecology, 1988. Trends Ecol Evol.
33. Prescott GW, Sutherland WJ, Aguirre D, et al. Political transition and emergent forest-conservation issues in Myanmar. Conserv Biol. 2017;00:1–14. https://doi.org/10.1111/cobi.13021.
34. R Core Team. (2020) R: A Language and Environment for Statistical Computing.
35. Sampson C, McEvoy J, Oo ZMZM, et al. New elephant crisis in Asia—Early warning signs from Myanmar. PLoS One. 2018;13:1–13. https://doi.org/10.1371/journal.pone.0194113.
36. Santiapillai C, Jackson P. The Asian elephant: an action plan for its conservation. Gland: IUCN; 1990.
37. Seidel DP, Dougherty E, Carlson C, Getz WM. Ecological metrics and methods for GPS movement data. Int J Geogr Inf Sci. 2018;32:2272–93. https://doi.org/10.1080/13658816.2018.1498097.
38. Shaffer LJ, Khadka KK, Van Den Hoek J, Naithani KJ. Human-elephant conflict: A review of current management strategies and future directions. Front Ecol Evol. 2019;6:1–12. https://doi.org/10.3389/fevo.2018.00235.
39. Sikes RS. 2016 Guidelines of the American Society of Mammalogists for the use of wild mammals in research and education. J Mammal. 2016;97:663–88. https://doi.org/10.1093/jmammal/gyw078.
40. Sodhi NS, Koh LP, Brook BW, Ng PKL. Southeast Asian biodiversity: An impending disaster. Trends Ecol Evol. 2004;19:654–60. https://doi.org/10.1016/j.tree.2004.09.006.
41. Songer M, Aung M, Allendorf TD, et al (2016) Drivers of Change in Myanmar’s Wild Elephant Distribution. Trop Conserv Sci 9:. https://doi.org/10.1177/1940082916673749.

42. Sukumar R. Ecology of the asian elephant in southern india. i. movement and habitat utilization patterns. J Trop Ecol. 1989;5:1–18. https://doi.org/10.1017/S0266467400003175.
43. Sukumar R. Ecology of the Asian elephant in southern India. II. Feeding habits and crop raiding patterns. J Trop Ecol. 1990;6:33–53. https://doi.org/10.1017/S0266467400004004.
44. Sukumar R. (2003) The Living Elephants.
45. Tucker MA, Böhning-gaese K, Fagan WF, et al. Moving in the Anthropocene: Global reductions in terrestrial mammalian movements. Science. 2018;469:466–9.
46. Wadey J, Beyer HL, Saaban S, et al. Why did the elephant cross the road? The complex response of wild elephants to a major road in Peninsular Malaysia. Biol Conserv. 2018;218:91–8. https://doi.org/10.1016/j.biocon.2017.11.036.
47. Wall J, Wittemyer G, Lemay V, et al (2014) Elliptical Time-Density model to estimate wildlife utilization distributions. Methods Ecol Evol 5:. https://doi.org/10.1111/2041-210X.12218.
48. Webber CE, Sereivathana T, Maltby MP, Lee PC. Elephant crop-raiding and human-elephant conflict in Cambodia: Crop selection and seasonal timings of raids. Oryx. 2011;45:243–51. https://doi.org/10.1017/S0030605310000335.
49. Wickham H. (2011) ggplot2. Wiley Interdiscip Rev Comput Stat. https://doi.org/10.1002/wics.147.
50. Wickham H, François R, Henry L, Müller K. (2018) Package “dplyr”.
51. Wittemyer G, Northrup JM, Bastille-Rousseau G. (2019) Behavioural valuation of landscapes using movement data. Philos. Trans. R. Soc. B Biol. Sci.

# Tables

Table 1
Description of landscape metrics used in this study. (Hesselbarth et al. 2019)

| Abbreviations | Full name | Metric Type | Description |
|---|---|---|---|
| frac_mn_* | mean fractal dimension index | Shape | Fractal dimension based on the patch perimeter and patch area: value (x) approaches 1 if all patches are squared and 2 if all patches are irregular |
| frac_sd_* | standard deviation of fractal dimension index | Shape | Standard deviation of the fractal dimension index, where x = 0 if the fractal dimension index is identical for all patches and increases without limit as the variation of the fractal dimension indices increases. |
| para_mn_* | mean perimeter to area ratio | Shape | A patch complexity metric that approaches 0 if the perimeter-to-area ratio for each patch approaches 0 (i.e. the form approaches a rather small square) and increases without limit, as perimeter-to-area ratio increases (patches become more complex). |
| para_cv_* | coefficient of variation of perimeter to area ratio | Shape | Coefficient of variation of perimeter-area ratio where x = 0 if the perimeter-area ratio is identical for all patches and increases without limit as the variation of the perimeter-area ratio increases. |
| para_sd_* | standard deviation of perimeter to area ratio | Shape | Standard deviation of perimeter-area ratio where x = 0 if perimeter-to-area ratio is identical for all patches and increases without limit as the variation of the perimeter-area ratio increases. This is scale dependent. |
| area_cv_* | coefficient of variation of patch area | Area and Edge | Summarizes variation in patch area where x = 0 if all the patches are identical in size and increases without limit as the variation of patch area increases in the landscape. |
| area_mn_* | mean patch area | Area and Edge | This is the simplest metrics – mean patch area of a given class. If all patches are small, x = 0 and increases without limit as the patch areas increases. |
| pland_* | percentage of landscape | Area and Edge | Characterizes the composition of the landscape as percentage of class *. When the proportional class area is decreasing, the value approaches 0. The metric is equal to 100 when only one patch is present on the landscape. |
| pd_* | patch density | Aggregation | Describes the fragmentation of the class as patch density where x approaches 0 as the proportional class area decreases. It is equal to 100 when only one patch is present. It is standardized to 100 hectares area. |

| Abbreviations | Full name | Metric Type | Description |
|---|---|---|---|
| dcore_mn_* | mean number of disjunct core area | Core area | This counts the disjunct core areas, whereby a core area is a patch within the patch containing only core cells. If ncore = 0 for all patches, x = 0 and increases without limit as the number of disjunct core area increases. |
| dcad_* | disjunct core area density | Core area | This is the number of disjunct core areas per ha relative to the total area. When no patch of class * contains a disjunct core area, x = 0, and increases without limit as disjunct core areas become more present (i.e. patches becoming larger and less complex). |
| ed_* | edge density | Area and Edge | Describes the configuration of the landscape as the sum of all edges of class * in relation to the landscape area. If only one patch is present, x = 0, and increases without limit as the landscape becomes more patchy. |
| lsi_* | landscape shape index | Aggregation | Metric based on actual edges and minimum hypothetical edges. When only one squared patch is present or all patches are maximally aggregated, x = 1, and increases without limit as the length of the actual edges increases (i.e. the patches become less compact). |

Table 2

Candidate model set for 95% AKDE dry season range showing the performance of the top model relative to others in the model set. The top model is composed of three landscape metrics describing configuration and composition of agriculture and one regarding natural vegetation composition within the range.

| Model | Predictor Variables | AICc | K | dAICc | Likelihood | AICc Weights |
|---|---|---|---|---|---|---|
| M_Ag_Nv_1 | (Intercept) + pland_ag + frac_mn_ag + ed_ag + area_cv_natveg | 335.87 | 5.00 | 0.00 | 1.00 | 0.87 |
| M_Ag_Nv_2 | (Intercept) + pland_ag + I(pland_ag^2) + frac_mn_ag + ed_ag + area_cv_natveg | 339.63 | 6.00 | 3.76 | 0.15 | 0.13 |
| M_Global | (Intercept) + area_cv_natveg + ed_ag + pland_ag + I(pland_ag^2) + dcore_mn_water + frac_mn_ag + para_mn_natveg + para_mn_water | 352.51 | 9.00 | 16.64 | 0.00 | 0.00 |
| M_Ag_Nv_3 | (Intercept) + ed_ag + pland_ag + area_cv_natveg | 358.49 | 4.00 | 22.62 | 0.00 | 0.00 |
| M_Nv_W_2 | (Intercept) + area_cv_natveg + para_mn_water | 365.97 | 3.00 | 30.10 | 0.00 | 0.00 |
| M_Nv_W_1 | (Intercept) + area_cv_natveg + para_mn_water + dcore_mn_water | 368.85 | 4.00 | 32.98 | 0.00 | 0.00 |
| M_Ag_W_1 | (Intercept) + pland_ag + frac_mn_ag + ed_ag + para_mn_water + dcore_mn_water | 396.57 | 6.00 | 60.70 | 0.00 | 0.00 |
| M_Null | (Intercept) | 403.88 | 1.00 | 68.01 | 0.00 | 0.00 |
| M_Ag_W_2 | (Intercept) + pland_ag + frac_mn_ag + ed_ag + para_mn_water | 405.26 | 5.00 | 69.39 | 0.00 | 0.00 |
| M_Water | (Intercept) + para_mn_water + dcore_mn_water | 405.53 | 3.00 | 69.66 | 0.00 | 0.00 |
| M_Ag_2 | (Intercept) + pland_ag + I(pland_ag^2) + frac_mn_ag + ed_ag | 407.11 | 5.00 | 71.24 | 0.00 | 0.00 |
| M_Ag_1 | (Intercept) + pland_ag + frac_mn_ag + ed_ag | 408.19 | 4.00 | 72.32 | 0.00 | 0.00 |

Table 3
Candidate model set for 50% AKDE dry season showing the top model carrying the majority of the model set weight (85.28%) composed of one metric describing the shape of the agriculture patches and three metrics describing shape and configuration of natural vegetation patches within the range.

| Model | variables | AICc | K | dAICc | Likelihood | AICc weights |
|---|---|---|---|---|---|---|
| M_Ag_Nv_2 | (Intercept) + lsi_ag + dcad_natveg + dcore_mn_natveg + para_mn_natveg | 281.51 | 5.00 | 0.00 | 1.00 | 0.85 |
| M_Global | (Intercept) + dcad_natveg + dcore_mn_natveg + para_mn_natveg + area_mn_natveg + lsi_ag | 285.31 | 6.00 | 3.80 | 0.15 | 0.13 |
| M_Ag_Nv_3 | (Intercept) + lsi_ag + dcore_mn_natveg + dcad_natveg | 289.22 | 4.00 | 7.71 | 0.02 | 0.02 |
| M_Ag_Nv_1 | (Intercept) + lsi_ag + dcore_mn_natveg | 294.41 | 3.00 | 12.90 | 0.00 | 0.00 |
| M_Ag | (Intercept) + lsi_ag | 297.74 | 2.00 | 16.23 | 0.00 | 0.00 |
| M_Nv_4 | (Intercept) + dcad_natveg | 324.97 | 2.00 | 43.46 | 0.00 | 0.00 |
| M_Nv_3 | (Intercept) + dcad_natveg + dcore_mn_natveg | 325.87 | 3.00 | 44.36 | 0.00 | 0.00 |
| M_Null | (Intercept) | 328.00 | 1.00 | 46.49 | 0.00 | 0.00 |
| M_Nv_2 | (Intercept) + dcad_natveg + dcore_mn_natveg + para_mn_natveg | 328.18 | 4.00 | 46.67 | 0.00 | 0.00 |
| M_Nv_1 | (Intercept) + dcad_natveg + dcore_mn_natveg + para_mn_natveg + area_mn_natveg | 330.09 | 5.00 | 48.58 | 0.00 | 0.00 |

Table 4

Candidate model set for average daily distance moved showing percentage of agriculture present within the 50% AKDE dry season range was the best variable examined at explaining the variation in mean average daily distance moved by the elephants during the dry season.

| Model | Variables | AICc | K | dAICc |
|---|---|---|---|---|
| M_3 | (Intercept) + pland_ag | 93.6200 | 2.00 | 0.00 |
| M_Null | (Intercept) | 96.07 | 1.00 | 2.45 |
| M_4 | (Intercept) + pland_ag + Sexmale | 96.20 | 3.00 | 2.58 |
| M_1 | (Intercept) + pland_ag + para_mn_ag | 96.43 | 3.00 | 2.81 |
| M_2 | (Intercept) + pland_ag + site1 + site3 | 98.31 | 4.00 | 4.69 |
| M_Global | (Intercept) + pland_ag + site1 + site3 + para_mn_ag | 98.88 | 5.00 | 5.26 |

Table 5
Calculated 95 percent minimum convex polygon area in squared kilometers for dry season, wet season and annual range.

| ID | Dry Year | Dry MCP 95% | Wet Year | Wet MCP 95% | Annual MCP 95% |
|---|---|---|---|---|---|
| 17104 | 2017_2018 | 244.8 | 2017 | 243.1 | 302.7 |
| 17104 | 2017_2018 | 244.8 | 2018 | 164.7 | 302.7 |
| 17105 | 2017_2018 | 109.3 | 2017 | 100.9 | 284.1 |
| 19970 | 2016_2017 | 105.9 | 2016 | 200.2 | 340.2 |
| 19971 | 2016_2017 | 201.7 | 2016 | 240.9 | 1153.0 |
| 22912 | 2017_2018 | 229.2 | 2017 | 113.4 | 575.1 |
| 22912 | 2016_2017 | 91.3 | 2018 | 128.7 | 575.1 |
| IRI2016-3121 | 2019_2020 | 57.3 | NA | NA | NA |
| IRI2016-3122 | 2019_2020 | 50.8 | NA | NA | NA |
| IRI2016-3123 | 2019_2020 | 184.3 | NA | NA | NA |
| IRI2016-3124 | 2019_2020 | 292.1 | NA | NA | NA |
| IRI2016-3125 | 2019_2020 | 89.2 | NA | NA | NA |
| ST2010-2594 | 2017_2018 | 14.3 | NA | NA | NA |
| ST2010-2707 | 2017_2018 | 132.4 | 2018 | 141.1 | NA |
| ST2010-2710 | 2017_2018 | 191.2 | NA | NA | NA |
| ST2010-2710-REDEPLOY | 2018_2019 | 150.6 | NA | NA | NA |
| ST2010-2711 | 2017_2018 | 139.9 | NA | NA | NA |
| ST2010-2713 | 2017_2018 | 61.7 | NA | NA | NA |
| ST2010-2714-REDEPLOY | 2018_2019 | 180.9 | NA | NA | NA |
| ST2010-2716 | 2018_2019 | 74.1 | 2019 | 27.9 | 65.8 |
| ST2010-2716 | 2019_2020 | 77.4 | 2019 | 27.9 | 65.8 |
| ST2010-2853 | 2018_2019 | 82.3 | NA | NA | NA |
| ST2010-2854 | 2018_2019 | 31.3 | 2019 | 26.8 | NA |
| ST2010-2855 | 2018_2019 | 113.6 | 2019 | 160.3 | 262.4 |
| ST2010-2855 | 2019_2020 | 78.9 | 2019 | 160.3 | 262.4 |

| ID | Dry Year | Dry MCP 95% | Wet Year | Wet MCP 95% | Annual MCP 95% |
|---|---|---|---|---|---|
| ST2010-2856 | 2018_2019 | 188.4 | 2019 | 239.6 | 678.8 |
| ST2010-2856 | 2019_2020 | 184.8 | 2019 | 239.6 | 678.8 |
| | **Average** | 129.14 | | 170.27 | 492.97 |

# Figures

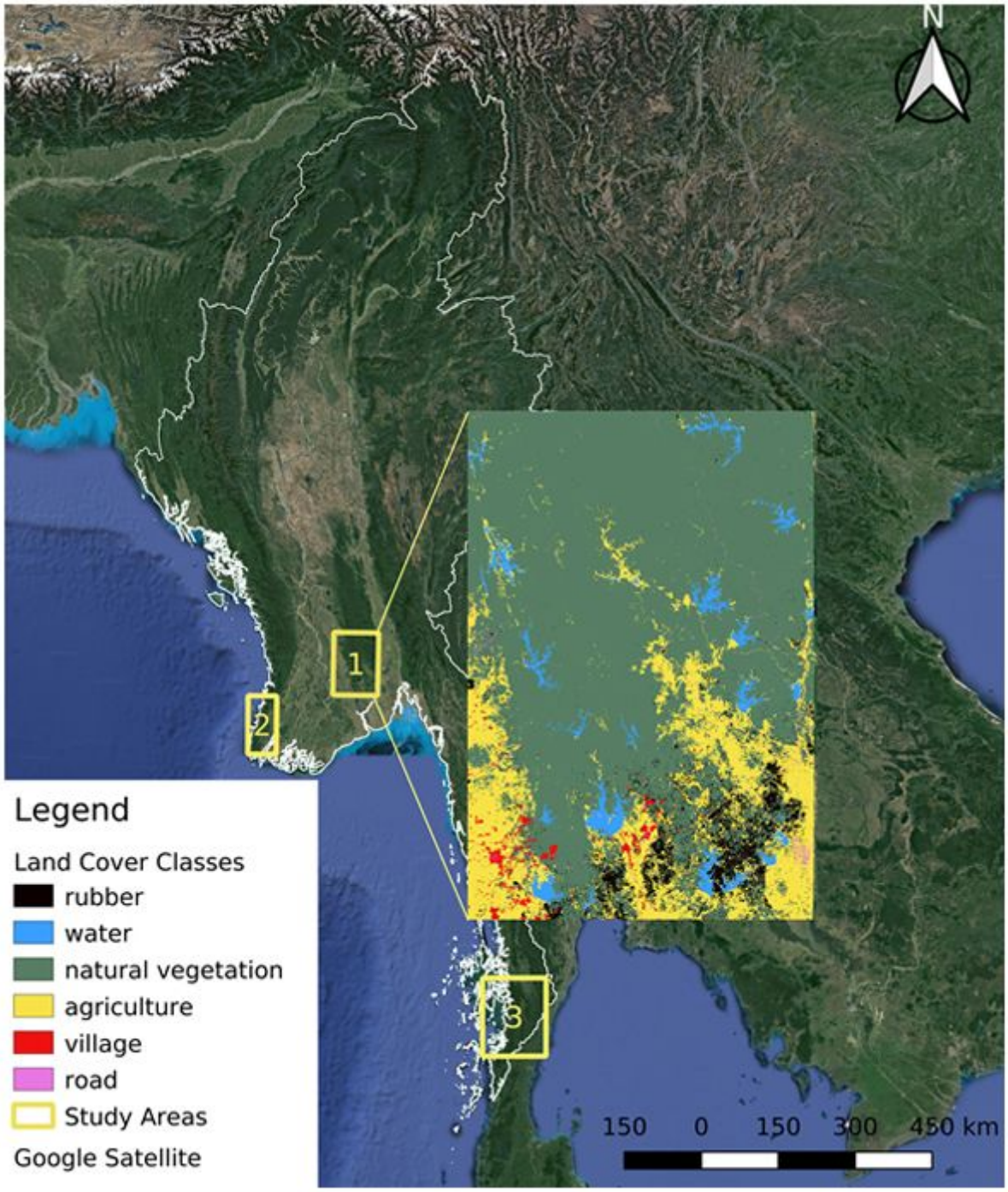



**Figure 1**

The location of the three study areas in Myanmar: Site 1 located on the foothills of bago yoma mountain range, site 2 located within the Ayeyarwaddy delta region, and site 3 part of Dawna Tanintharyi Mountain Range. The insert shows the land cover map for site 1 from which various landscape metrics were derived for analysis of range conditions. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

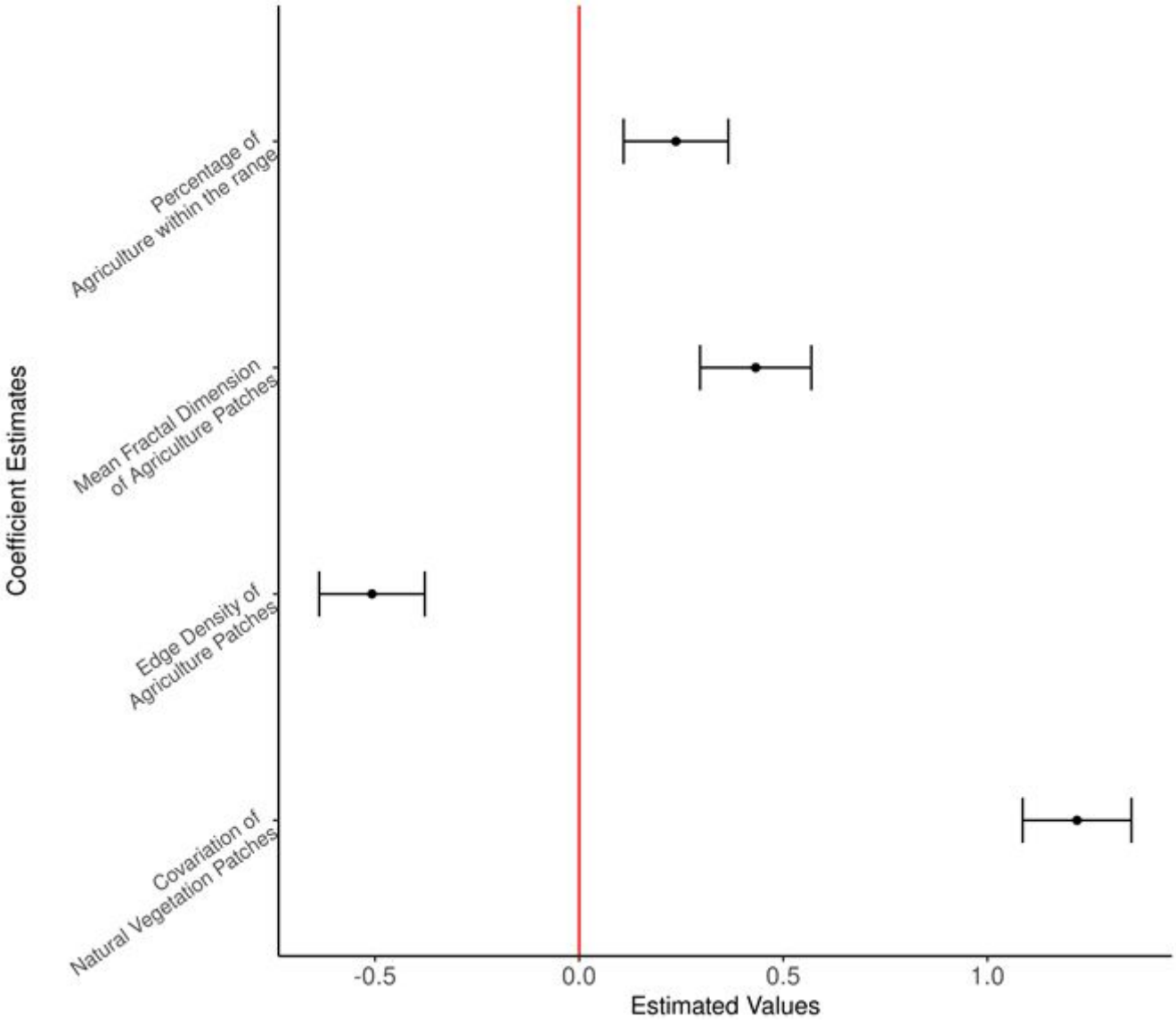
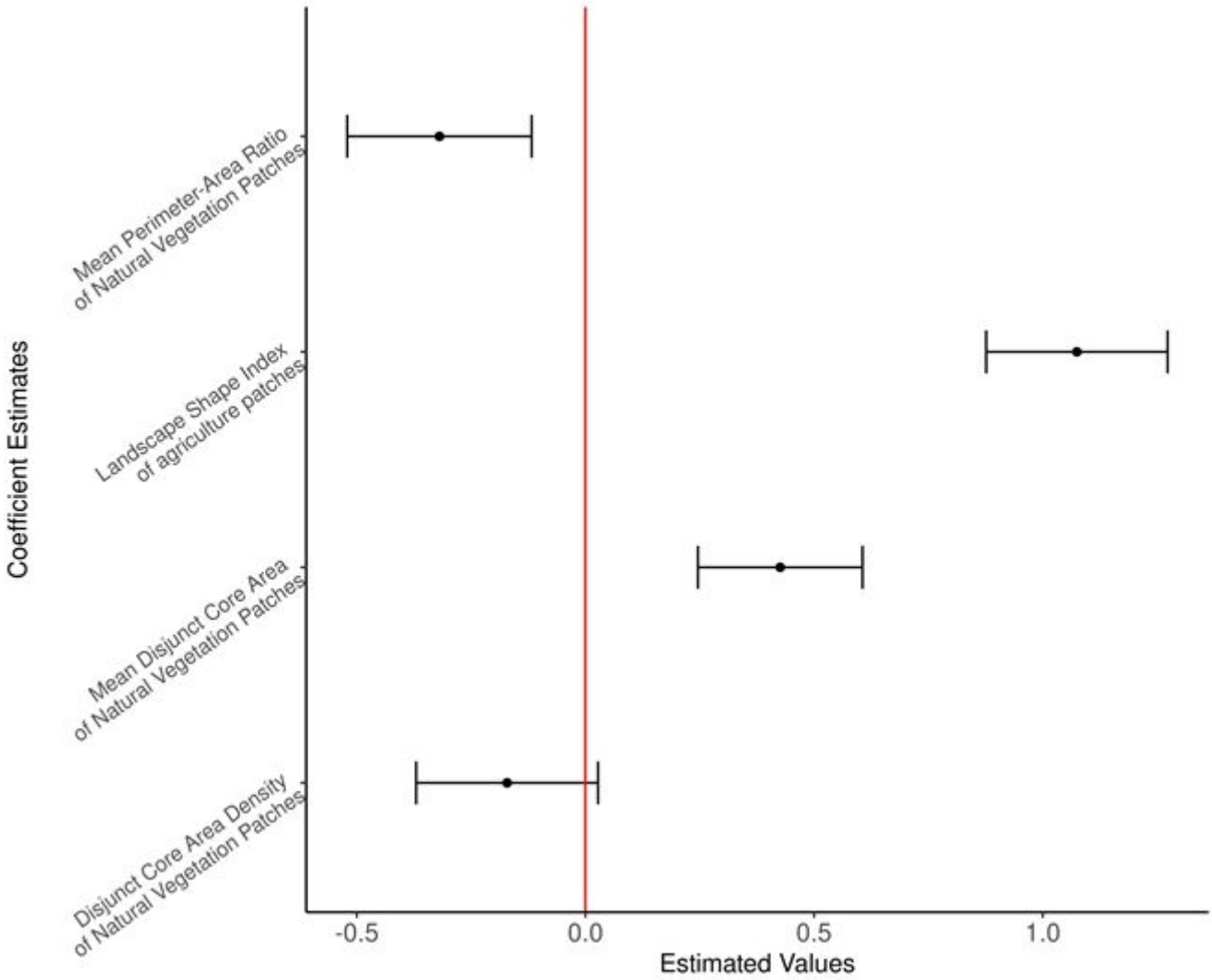


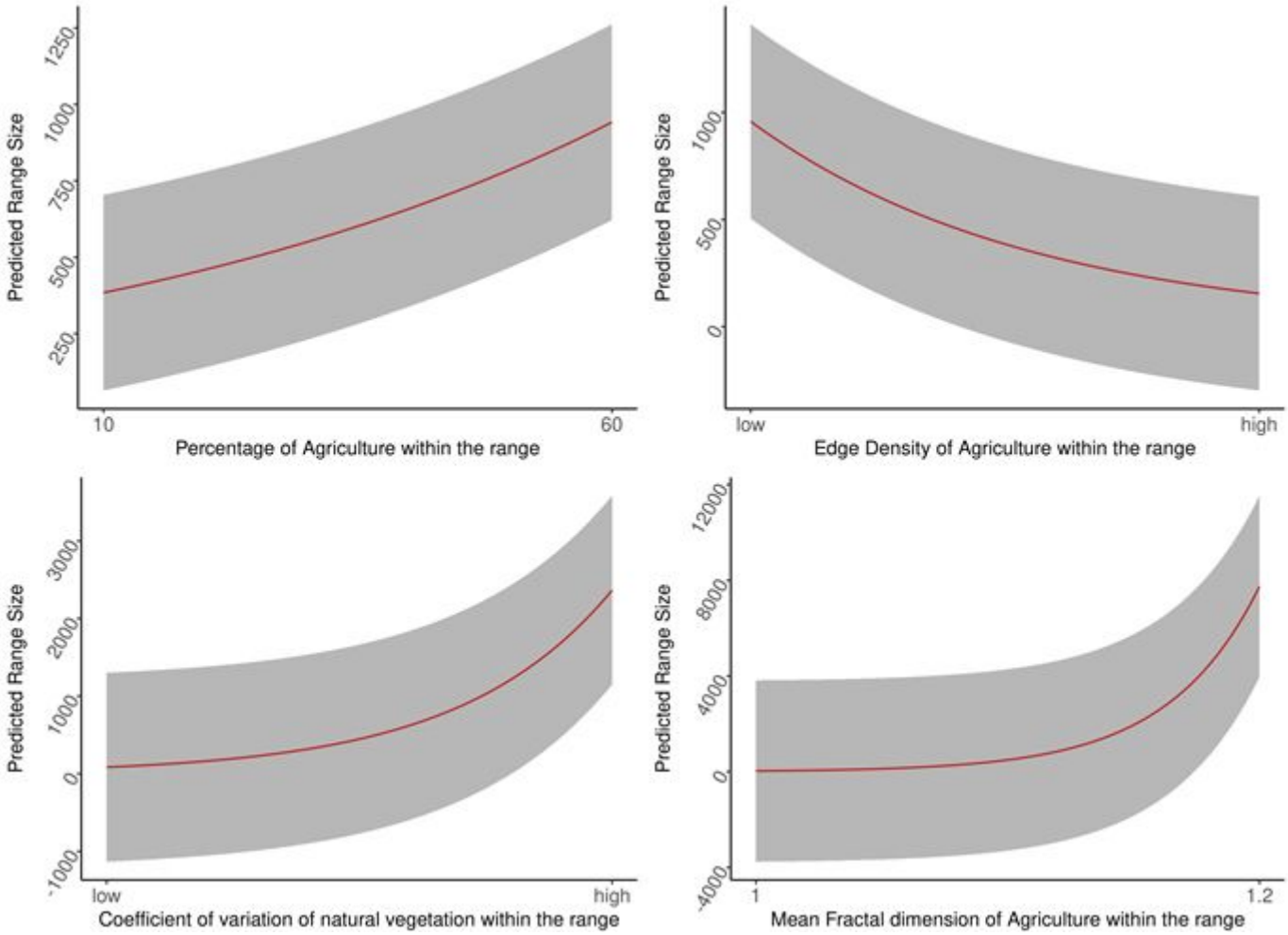

**Figure 2**

Estimated coefficient values from the top model of dry season 95% AKDE range showing landscape metrics describing the patterns of agriculture and variability in natural vegetation cover were the important independent variables in explaining variation in range size.



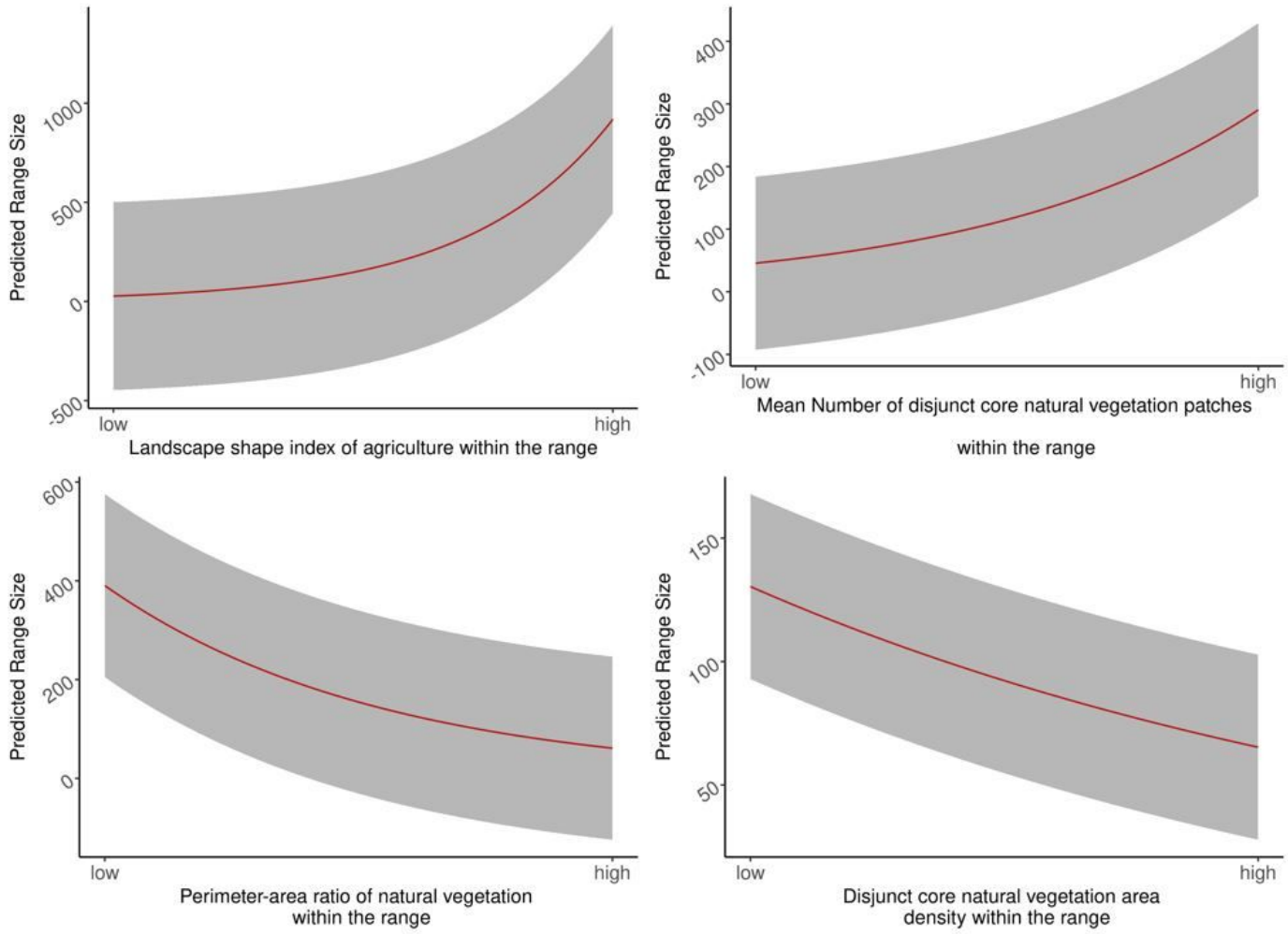

## Figure 3

Estimated coefficient values from the top model of dry season 50% AKDE range showing landscape shape index for agriculture and several metrics representing natural vegetative constitution were the covariate explaining variation in range size.




## Figure 4

Functional relationship between the estimated regression coefficients of the top predictive landscape metrics and the 95% AKDE range size. Predicted range size for elephants during the dry season increased as the landscape becomes more patchy.




## Figure 5

Functional relationship between the estimated regression coefficients of the top predictive landscape metrics of the 50% AKDE range size. Predicted range size for elephants during the dry season increased as the index of agriculture shape (i.e., agricultural boundary length) increased and decreased where more intact natural vegetation was found.