

Optimizing the positioning of wildlife crossing structures using GPS telemetry

Guillaume Bastille-Rousseau^{1,2}  | Jake Wall² | Iain Douglas-Hamilton² | George Wittemyer^{1,2}

¹Department of Fish, Wildlife, and Conservation Biology, Colorado State University, Fort Collins, CO, USA

²Save the Elephants, Nairobi, Kenya

Correspondence

Guillaume Bastille-Rousseau
Email: gbr@colostate.edu

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Abstract

1. Development of transportation corridors has accelerated globally, with infrastructure projects being implemented across remote ecosystems, particularly in the tropics. Such developments can have negative impacts on wildlife and their ecosystems. The importance of wildlife crossing structures to mitigate adverse effects of such features is widely recognized, but the siting of and investment in crossing structures is contentious. Data on animal movement provide valuable, highly specific information for such processes, but can present analytical challenges and remain underutilized in planning mitigation efforts.
2. We develop two algorithms based on Integer Linear Programming to prioritize crossing points based on frequency of use or breadth of coverage among tracked individuals. These scenarios represent metrics likely to guide the planning of crossing structures, where the former may relate to the objective of minimizing vehicle-animal collisions and the latter on maintaining ecosystem connectivity. We exemplify the algorithms through application on a tracking dataset from over 150 African elephants living near the proposed Lamu Port-South Sudan-Ethiopia-Transport corridor. We explore the influence of sampling bias on outcomes and discuss considerations to guide the application process.
3. Given the generally open, unfenced nature of this ecosystem, recorded movements occurred throughout the system and a third of the corridor length in the ecosystem was intersected by recorded elephant movements. The selection of crossing structure locations and their impacts on elephants varied whether we used a subsample of elephant representative of local population density or total sample of monitored individuals. The two algorithms also selected for different crossing structure locations.
4. *Synthesis and applications.* Our work shows some of the challenges of using Global Positioning System telemetry in deciding where to put crossing structures and demonstrates the need to identify the type of constraints in the system and desired crossing structure characteristics a priori. We recommend managers carefully evaluate the presence of potential biases in their data. High-resolution data combined with objective prioritization methods allow reasoned planning actions, but are often lacking during critical infrastructure planning stages. Given the

limited budget already allocated to mitigation measures in most proposed developments, the tools developed and applied here can facilitate effective spatial planning.

KEYWORDS

African elephant, animal movement, development corridors, GPS telemetry, habitat connectivity, integer linear programming, spatial planning, wildlife crossing structures

1 | INTRODUCTION

With global development expanding the human footprint, landscape conversion and habitat loss are the most prevalent drivers of population decline and key risk factors for species persistence (Brook, Sodhi, & Bradshaw, 2008). Landscape conversion occurs in many different shades, from the most overt systematic alteration of the topology, hydrology and vegetative structure of an area to more nuanced changes that leaves much of the native community in place. While nuanced developments tend to get less attention, they can have serious ecological ramifications. Linear infrastructure development, including transportation and economic corridors, in particular is recognized to have outsized ecological impacts relative to their small physical footprints, flagging these types of developments as of increasing conservation relevance and concern (Fahrig & Rytwinski, 2009). The potential impacts on wildlife species and ecosystem functioning caused by human-made linear features (LF) (roads, railways, power lines or pipelines) are a result of fragmentation of habitat, facilitation of exotic species invasion and alteration of community interactions (Fahrig & Rytwinski, 2009).

Infrastructure development and, in particular, associated LF can interfere with the movement and behaviour of wildlife (Eftestøl, Tsegaye, Herfindal, Flydal, & Colman, 2014; Frair et al., 2005), resulting in changes in wildlife distribution and abundance (Fahrig & Rytwinski, 2009). For some herbivores, the edge effects and canopy openings caused by LF can enhance food availability and access (Gill, Norris, Gill, & Sutherland, 2001; Small & Hunter, 1988), but may also enhance predator efficiency and alter critical interspecies interactions (James & Stuart-Smith, 2000; Whittington et al., 2011). LF can increase human access to areas, which can have adverse effects on wildlife populations (Northrup et al., 2012), and can directly increase mortality of wildlife and increase risks to humans through vehicle collisions (Neumann et al., 2012). In addition to direct demographic effects, LF can act as impermeable barriers, reducing gene flow among meta-populations by limiting the dispersal of individuals, or creating small population dynamics in isolated patches (Rico, Kindlmann, & Sedláček, 2009). Mitigating the negative impacts of infrastructure development on wildlife movement and ecosystem connectivity is critical to the persistence of animal populations and the maintenance of key ecosystem processes (Beyer et al., 2016).

Given these identified problems, approaches to incorporate ecological datasets in planning for the siting and structure of such

features are critical. Crossing structures (e.g. overpass bridges or underpass tunnels) are the favoured mitigation measures to reduce wildlife-vehicle collisions and maintain connectivity (Clevenger & Huijser, 2011). However, high-costs limit the number of these crossings, given the limited budget allocated to these structures. It is therefore critical that the location of these structures optimizes their effectiveness in mitigating the negative impacts of developments. Fine-scale data on wildlife movement, such as Global Positioning System (GPS) telemetry, can provide an invaluable tool in identifying areas of importance for connectivity along a LF (Horne, Garton, Krone, & Lewis, 2007), but surprisingly, such data are rarely used during planning. GPS telemetry can present analytical challenges when applied to identifying wildlife crossings; one issue being that the degree to which the sample of GPS monitored individuals is spatially and behaviourally representative of the population. Additionally, the limited application of GPS telemetry may be related to the lack of objective tools to optimize crossing structure positioning (see Downs et al., 2014; Loraamm & Downs, 2016).

In sub-Saharan Africa, over 53,000 km of developments corridors have been proposed or are being created with the goal of increasing agricultural production, natural resources extraction and overall economic growth (Laurance, Sloan, Weng, & Sayer, 2015; Weng et al., 2013). These proposed corridors will bisect over 2,000 African protected areas and other areas containing high wildlife abundances (Laurance et al., 2015), making identification of key crossing points of paramount importance to conservation mitigation efforts. Here, we develop approaches using GPS tracking data to quantify the importance and optimize the selection of locations along infrastructure developments for the establishment of wildlife crossings. We exemplify the utility of these approaches through application on an extensive tracking dataset from over 150 African elephants living near the planned Lamu Port-South Sudan-Ethiopia-Transport (LAPSSET) corridor, one of the proposed sub-Saharan development corridors in northern Kenya. We develop two analytical approaches for assisting in localizing potential crossing structures: the first identifies the heaviest used crossing points in a given area (i.e. the relative use and spatial distribution of the identified crossing locations), and the second maximizes access to crossing structures by the largest number of individuals (i.e. coverage). We compare application of these approaches to two different elephant population sampling strategies to investigate how sampling bias may impact results. Finally, we discuss the utility of our algorithms within various

management contexts. We include all functions developed for the analyses in the free R package “wildxing” to facilitate the use of our approach by wildlife managers and decision makers.

2 | MATERIALS AND METHODS

2.1 | Study area

The Laikipia/Samburu ecosystem in northern Kenya is inhabited by the country's second largest elephant population as well as several other species of concern including the critically endangered Grevy's zebra (*Equus Grevy's*). The elephant population is of conservation interest, and has been designated one of the Convention on International Trade in Endangered Species (CITES) Monitoring of Illegal Killing of Elephants (MIKE) sites (Wittemyer et al., 2014). The MIKE site, designed to envelop the majority of the elephant populations range, is located at approximately 0.4°S to 2°N, 36.2°E to 38.3°E, covering an area of approximately 34,000 km² (Figure 1). Land use in the area varies from private and communal ranches to government forest and national wildlife reserves. The area has a variety of habitats, including cool moist highland forests and semi-arid savanna. Long-distance movements of both wildlife and livestock are common in order to access regions of higher vegetation productivity driven by spatially stochastic rainfall

(Raizman, Rasmussen, King, Ihwagi, & Douglas-Hamilton, 2013; Wittemyer, Getz, Vollrath, & Douglas-Hamilton, 2007).

Our analysis is focused on a preliminary, proposed section of the LAPSSET commerce corridor in and around the Samburu and Buffalo Springs National Reserves Complex (lying approximately 0.5°N, 37.5°E, Figure 1). The development of this transport and infrastructure project will include the construction of railways to the capitals of South Sudan and Ethiopia, a road network, oil pipelines, airports, ports, oil refineries and three resort cities (Figure 1). Projected routes will bisect the middle of the ecosystem.

2.2 | Data collection

We analysed GPS data collected since 1998 from 156 elephants in this area as part of a long-term research project (Wittemyer, Daballen, & Douglas-Hamilton, 2013). Due to collar failures, technical advances and project funding, collaring efforts have fluctuated during this period. Elephants have a complex group structure including stable families that normally travel as a group, from which males disperse at maturity (Wittemyer, Douglas-Hamilton, & Getz, 2005). As a result, GPS data collected from females represent a family unit of between 9 and 15 individuals and males typically represent a single individual. On one occasion, more than one elephant was tracked simultaneously from the same family, which we controlled

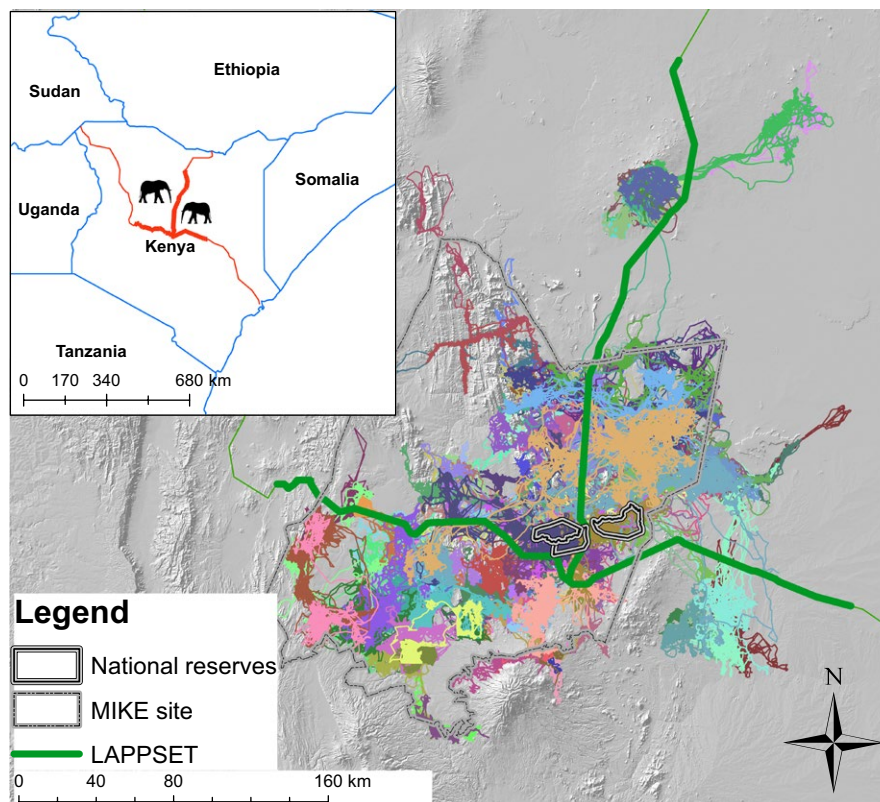


FIGURE 1 The proposed Lamu Port-South Sudan-Ethiopia-Transport (LAPSSET) Corridor project will bisect critical wildlife areas in northern Kenya. We focused on a section (bold) of the railway corridor near a Convention on International Trade in Endangered Species (CITES) Monitoring of Illegal Killing of Elephants (MIKE) site and near three national reserves where over 150 elephants were tracked (represented as thin lines)

for by excluding one of the individuals for this analysis. Erroneous locations were filtered by using a speed-filter of 9 km/hr (similar to Wall, Wittemyer, Klinkenberg, LeMay, & Douglas-Hamilton, 2013). Individual elephant tracking datasets averaged 22,879 locations (range 179–142,654) with a total sample of 3,591,945 locations. GPS locations were converted into trajectories where a step is the straight line between two consecutive locations. Only steps where the time interval between two locations was less than 24 hr were included in the analysis, so that very uncertain movement steps were not included in the analysis. These data represent a large, but potentially spatially biased sample because many collars were deployed within national reserves.

We therefore conducted a parallel analysis on a subset of the total dataset comprised of 40 individuals collared in 2014–2015 where collars were deployed systematically across the MIKE site. These GPS locations are representative of elephant density in the ecosystem as characterized by aerial survey data collected in 2002, 2008 and 2012 and locations of natural mortality collected as part of the MIKE ecosystem wide monitoring program (Ihwagi et al., 2015). This dataset can be considered spatially unbiased.

2.3 | Quantifying use of crossing sections of the infrastructure corridor

To identify critical crossing points along the proposed railways, we divided the LAPSET corridor into consecutive 200 m long segments ($n = 3,165$), evaluated whether an elephant used the segment, and tallied the number of steps for each elephant that crossed (intersected) the segment. We also calculated a standardized crossing intensity metric C for each segment (s) following:

$$C_s = \frac{\sum_{i=1}^{n_s} \frac{x_{is}}{t_i}}{n_s}$$

where C_s is the standardized crossing intensity for segment s , x_{is} is the number of steps from individual i that crossed segment s , t_i is the time over which the individual was monitored in days, and n_s is the number of different individuals crossing segment s . We tested if the calculation of this metric was sensitive to the number of individuals using the segment and found no correlation ($R = -.036$, $df = 1,065$, $p = .239$). This standardized metric accounted for variation in sampling frequency and length of monitoring among individuals and could potentially account for differential spatial sampling along the corridor (i.e. more individuals captured and followed in a given area). We tested this by looking at how the calculation of the crossing intensity metric differed whether using the full dataset or the systematically sampled subset.

Finally, we evaluated how the standardized crossing intensity metric compared to crossing points identified by community game scouts along a 40 km section of the proposed LAPSET corridor. The latter crossing points based on local knowledge were assessed by driving the road with local community scouts in June 2017. We compared the segments identified by community scouts as being

used or not to the standardized crossing intensity using a t test with unequal variances. To test if local knowledge more closely reflected recent crossing by elephants or longer term patterns, we performed the analysis using the total dataset including only the latest year of data (May 2016–June 2017).

2.4 | Optimization of crossing structure locations

We developed and applied two Integer Linear Programming algorithms to optimize the positioning of wildlife crossing structures. The first algorithm is based on the standardized crossing intensity metric and the spatial distribution of crossing structure locations (hereafter referred as the crossing intensity [CI] algorithm). The CI algorithm runs an optimization procedure where the importance of a segment's relative position (spatial spread from other crossing points) vs. the importance of intensity of use can be specified by the user in order to enhance the biological importance of identified crossing locations and insure selected segments are sufficiently far from each other (i.e. where both processes are weighted equally, identified crossings would be of high use and relatively distributed across the study area). The algorithm was developed to select the most important crossing points for elephants (i.e. those locations that were most heavily trafficked).

The second algorithm solves a typical maximum coverage location problem (referred hereafter to "MLCP algorithm"; Downs et al., 2014) where the selected segments will "cover" the greatest number of different individuals given each segment can serve up to a threshold distance. This algorithm differs from the former in that selected segments do not have to be used heavily, but can be in close proximity to multiple heavily used segments (i.e. proximity to paths is more important than the actual movements that happened across a given segment). In addition, both algorithms can adjust the optimization routine by incorporating natural crossings (e.g. a bridge over a river that is effectively a wildlife crossing point) or crossings specified a priori for human/economic reasons to adjust the final optimization solution. Further details about each algorithm are provided in Appendix S1.

As an illustration of each algorithm and to compare how they can differ, we created different scenarios that combined the representative and global datasets with each algorithm. For all scenarios, we identified five sites (i.e. development plans budgeted to build five crossings). For the CI algorithm, we gave equal weight to the spatial spread and intensity of use. For the MCLP algorithm, a threshold distance for the coverage of 5 km was selected. This means that segments within 5 km (on each side) of a structure are assumed to be covered by this structure (i.e. we assumed elephant would be willing to travel up to 5 km to reach a crossing structure given this is on the lower end of average daily displacements among the individuals tracked). We evaluated differences among scenarios by calculating the minimum average distance between each selected crossing (i.e. analogous to the Earth mover's distance statistic; Potts, Auger-Méthé, & Lewis, 2014). We also ran additional scenarios using each algorithm which are presented in Figures S1

and S2 in Appendix S2. All functions from our analysis (segmentation of LFs, home-range intersection, crossing intensity and optimization algorithms) and an explanatory vignette are available as an R package “wildxing” (<https://github.com/BastilleRousseau/wildxing>).

3 | RESULTS

Up to 33% of the segments were crossed by individuals in the total sample containing movements of 156 individual elephants, while 18% of the 200 m segments analysed along the LAPSSET corridor were crossed by the representative subset of 40 elephants (Figure 2). As calculated from the total sample, each segment was crossed by an average of 3.24 different individuals (range = 1–22, Figure 2d) an average of 6.37 times (range = 1–88). Using the representative subset dataset, each segment was crossed by an average of 1.45 different individuals (range = 1–7, Figure 2b) an average of 2.64 times (range = 1–53). The average standardized crossing intensity was 0.023 (range = 0.002–0.632, Figure 2c) for the total sample and 0.019 (range = 0.007–0.186, Figure 2a) for the subset. Overall, the standardized crossing intensity metric estimated from the sub-sample dataset showed moderate correlation with the metric calculated from the total sample ($R = .37$, $df = 2,411$, $p < .001$) but stronger

correlation with the number of individuals using a given segment ($R = .57$, $df = 2,411$, $p < .001$).

Comparison between the crossing segments identified through the optimization routine indicates that strong differentiation in crossing weighting occurred with the different emphases of the different routines (Figure 3). Using the CI algorithm, selected locations showed greater difference between the representative subset and the total sample (average distance = 36 km, Figure 3a,b) than when using the MCLP algorithm (average distance = 16 km, Figure 3c,d). Applying each algorithm to the same dataset also provided different results with average distance between selected crossing of 24 and 30 km for the representative (Figure 3a,c) and global (Figure 3b,d) datasets, respectively. Overall, the MCLP provided connectivity for a greater number of elephants (Figure 3). Modifying parameters of each scenario also resulted in a different set of selected locations (Figures S1 and S2), indicating the sensitivity of results to weighting.

Crossing segments identified using local knowledge were not significantly aligned with tracking data-based crossing intensity metrics, given that the segments considered as used based on local knowledge did not have a higher standardized crossing intensity ($t = -0.74668$, $p = .4602$, Figure 4a). Alignment was also not influenced by the timing of the tracking data (latest year of data; $t = -0.994$, $p = .348$; Figure 4b).

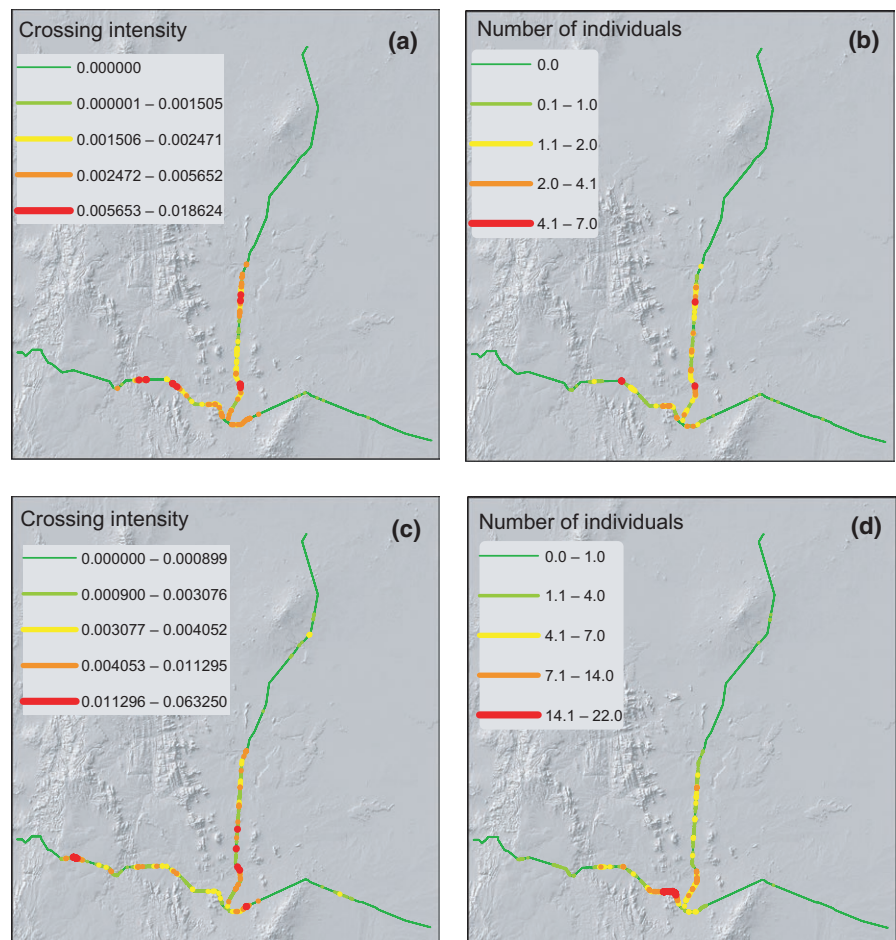


FIGURE 2 Subsection of the proposed Lamu Port-South Sudan-Ethiopia-Transport (LAPSSET) Corridor project. (a) Standardized crossing intensity of elephant with the LAPSSET corridor using a representative sample of 40 elephants (see Section 2). (b) Number of different elephants crossing each segment of the LAPSSET corridor using the representative sample of elephants. (c) Standardized crossing intensity of elephant with the LAPSSET corridor using all monitored individuals. (d) Number of different elephants crossing each segment of the LAPSSET corridor using all monitored individuals

4 | DISCUSSION

Mitigating the impacts of infrastructure corridors on wildlife is critical to reduce ecological impacts (Clevenger & Huijser, 2011), to enhance public safety (Olsson & Widen, 2008), and alleviate the need for costly retrofitting projects for future mitigation needs. To facilitate conservation planning in relation to the development of infrastructure projects, we developed simple and efficient approaches to analytically identify priority crossing locations from GPS tracking data. Such data are increasingly collected globally, and provide the highest spatio-temporal data on wildlife use that can be powerful for understanding and mitigating impacts from human land-use changes.

We applied these algorithms to an extensive radio tracking dataset collected on elephants inhabiting the Laikipia/Samburu ecosystem subject to a major infrastructure development project. African elephants were our target species given that they are a flagship and an umbrella species, whose protection can have significant positive impacts on other species (Epps, Mutayoba, Gwin, & Brashares, 2011) and ecosystem functioning (Haynes, 2012). Given the generally open, unfenced nature of this ecosystem, recorded movements occurred throughout the system and roughly a third of the corridor length in the ecosystem was intersected by recorded elephant movements (i.e. elephants crossed over the proposed route). The undeveloped nature of the study area affords a rare opportunity to

identify critical areas likely to be impacted by development a priori, but also presents a challenge given that wildlife movement is not constrained and most areas in the region are used by wildlife. As such, restricting focus to a handful of crossing locations is sensitive to the definition of one's criteria.

4.1 | Application of crossing algorithms

We developed two algorithms that highlight different features of the movement data and, ultimately, address different objectives when analysing these data. The first approach, the CI algorithm, is suited for situations where the specific crossing intensity is of interest along a LF. This is applicable to scenarios when the immediate crossing location is the unit of interest for planning, such as when attempting to mitigate vehicle-animal collisions or when crossing structures will have the biggest impacts by being placed in currently used locations as can occur when a LF will remain unfenced and/or represent a semi-permeable barrier. The second approach using the MCLP algorithm is suited for a limited-access scenario (e.g. fencing) where few crossing structures will be located at regular distances and connectivity restricted in all other locations. In the MCLP approach, the importance of the selected segment is not strongly weighted, rather, the focus is on identifying the segment that provides the greatest coverage for individuals that generally use an area. We assume this algorithm would be ideal for scenarios where fencing is used along

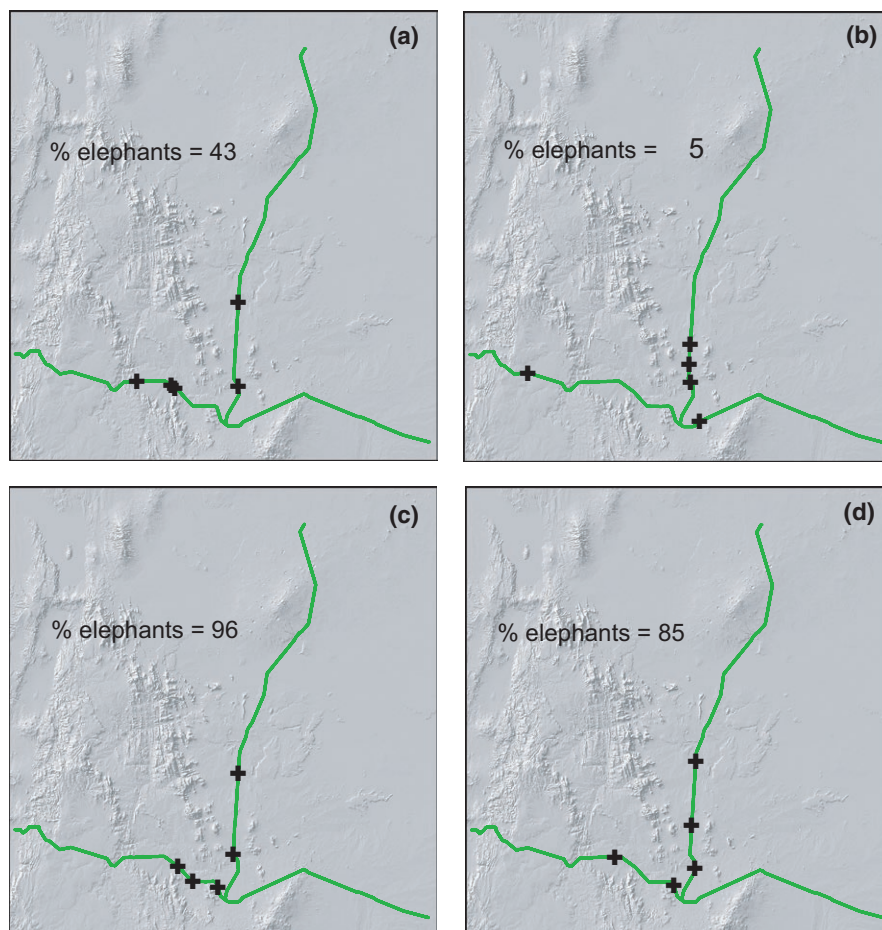


FIGURE 3 Optimization of crossing structures location along the Lamu Port-South Sudan-Ethiopia-Transport (LAPSET) corridor railways using the crossing intensity and maximum coverage location problem algorithms (see Section 2). (a) The crossing intensity (CI) algorithm selected the top five crossing segments based on equally weighting the influence of spatial spread and intensity of use in the optimization and using the subsample of data. (b) The scenario in (a) applied to the total dataset. (c) The maximum coverage location algorithm (MCLP) selected the top five crossing segments based on a threshold distance of 5 km and using the representative sample of individuals. (d) The scenario in (c) applied to the total dataset

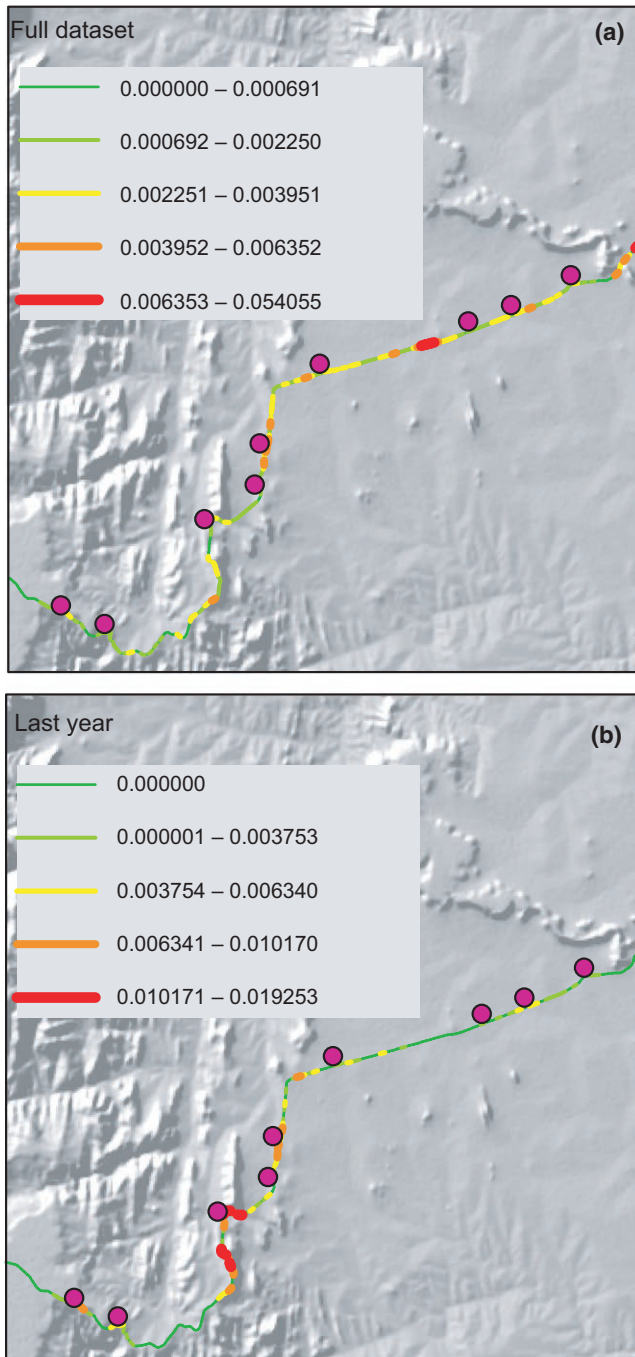


FIGURE 4 Elephant standardized crossing intensity estimated from GPS tracking data was compared with crossing points identified by local community scouts. (a) Communities identified crossing locations (dots) and standardized crossing intensity for 200 m segments of the road using GPS telemetry collected between 2001 and 2017. (b) Community scout identified crossing locations and standardized crossing metrics developed using GPS telemetry data collected June 2016–June 2017

LFs to funnel individuals into a given crossing point. Given the different nature of these two approaches and the diverging results they provide, it is critical that the user identifies the type of constraints in the system and desired crossing structure characteristics.

4.2 | Representativeness of GPS telemetry

Overall, the selection of crossing structure locations and their impacts on elephants varied whether we used the subsample or total sample of monitored individuals. This is concerning for the robustness of results reliant on GPS data to optimize crossing locations. Strong spatial bias in monitoring has the potential to impact the overall optimization, even if algorithm results are not clustered near the core of the spatially biased sample. We recommend managers carefully evaluate the presence of potential biases in their data, and subsample or weight individual data in manner that offers a representative dataset. The running of different scenarios, as exemplified here, can help decision makers understand the sensitivity of results to impose assumptions. However, the wide variation in results in the study area is likely related to the general and widely dispersed use of this unfenced ecosystem. Other systems with more development likely have greater restrictions on possible crossing points along a LF, which may require excluding segments from the optimization algorithm (both optimization functions available in the wildxing package include this option).

We also compared elephant crossing locations obtained from surveys with local communities to those identified using GPS telemetry data to contrast outcomes that result from different types of data. The locations of key crossing locations were not well matched across these two sources. Where tracking and community identified crossing locations coincided, the crossing intensity as measured by the tracking data was relatively low. This was irrespective of the timing of the GPS tracking data used to identify crossings. Community identified crossings were more likely to be found near villages or livestock paths. While GPS telemetry suffers from its own issues (discussed in the previous paragraph), our analysis suggests that community-based data are important where other sources are not available, but subject to biases related to human activities, and ideally would require more systematic surveying. Empirically collected data on animal activities may be more reliable when available.

4.3 | Additional considerations

Our algorithms allow multiple factors and motivations to be considered in selecting crossing locations. Our algorithms combining intensity of use and number of individuals represented are an improvement over existing approaches. Previous approaches typically summarized the general crossing behaviour, habitat selection or simply record intensity of use without subsequent optimization (Horne et al., 2007; Sawyer, Kauffman, Nielson, & Horne, 2009; Schuster, Römer, & Germain, 2013). Other approaches proposed optimization algorithms but without regard to sampling bias and spatial spread (Downs et al., 2014; Loraamm & Downs, 2016). Intensity of use may not be the only metric of value when quantifying the importance of a segment for wildlife movement. Approaches that consider the importance of a segment for specific types of movement (e.g. movement modes; Gurarie et al., 2016; Morales, Haydon,

Frair, Holsinger, & Fryxell, 2004) or provide insight to broader scale connectivity of a location (e.g. network metrics; Bastille-Rousseau, Douglas-Hamilton, Blake, Northrup, & Wittemyer, 2018; Wittemyer, Keating, Vollrath, & Douglas-Hamilton, 2017) could provide more refined identification of crossing locations in prioritization schemes. Likewise, approaches assessing connectivity for multiple species may be preferable where community or multispecies conservation goals are paramount (Mimet, Clauzel, & Foltête, 2016). We focus on a single species in this study, given the lack of comparable data from other species.

The increased pace of land-use change and ecosystem degradation poses serious threats to wildlife (Cardinale et al., 2012), demanding novel mitigation approaches. Solutions to mitigate land-use change are chronically underfunded (Lindsey, Balme, Funston, Henschel, & Hunter, 2016; Miller, 2014), requiring smart planning to maximize impact from limited resources (Kiesecker, Copeland, Pocewicz, & McKenney, 2010; Mandle et al., 2016). Decades of large mammal research have generated valuable data that can be applied to such tasks. High-resolution data combined with objective prioritization methods allow reasoned planning actions, but are often lacking during critical infrastructure planning stages. Instead, these decisions are frequently made subjectively, which can result in suboptimal use of funds directed towards conservation (Kareiva, Groves, & Marvier, 2014). Given the limited budget already allocated to mitigation measures in most proposed developments, tools that facilitate spatial planning are of high value.

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AUTHORS' CONTRIBUTIONS

G.W. and J.W. initially thought of the crossing count approach. G.B.R. developed the standardization, the optimization algorithm and the analytical framework (wildxing package). G.B.R. performed the analyses. I.D.H. and G.W. collected the elephant data. G.B.R. led the writing of the manuscript with contributions from G.W. All authors have commented and approved the final version of the manuscript.

DATA ACCESSIBILITY

Elephant tracking data have not been archived given their highly sensitive nature. Interested readers can contact the corresponding author directly for inquiries. Functions and associated documentation (which include examples) are available within the R package wildxing. <https://doi.org/10.5281/zenodo.1158705> (Bastille-Rousseau (2018).

ORCID

Guillaume Bastille-Rousseau  <http://orcid.org/0000-0001-6799-639X>

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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