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ARTICLE

Modelling habitat conversion in miombo woodlands: insights from Tanzania

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ABSTRACT
Understanding the drivers of natural habitat conversion is a major challenge, yet predicting where future losses may occur is crucial to preventing them. Here, we used Bayesian analysis to model spatio-temporal patterns of land-use/cover change in two protected areas designations and unclassified land in Tanzania using time-series satellite images. We further investigated the costs and benefits of preserving fragmenting habitat joining the two ecosystems over the next two decades. We reveal that habitat conversion is driven by human population, existing land-use systems and the road network. We also reveal the probability of habitat conversion to be higher in the least protected area category. Preservation of habitat linking the two ecosystems saving 1640 ha of land from conversion could store between 21,320 and 49,200 t of carbon in the next 20 years, with the potential for generating between US$ 85,280 and 131,200 assuming a REDD+ project is implemented.

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Spatio-temporal; land use; Bayesian; miombo; INLA; REDD

1. Introduction

High levels of natural habitat loss are a key conservation concern around the world, and they impact large mammal populations (Bailey, McCleery, Binford, & Zweig, 2016; Butchart et al., 2010; Craigie et al., 2010; DeFries, Hansen, Newton, & Hansen, 2005; Dirzo et al., 2014; Hansen & DeFries, 2007; Harris, Thirgood, Hopcraft, Cromsigt, & Berger, 2009; Jewitt, Goodman, Erasmus, O'Connor, & Witkowski, 2015; Krauss et al., 2010). These impacts not only contribute to species extinction (Rybicki & Hanski, 2013) but also interfere with ecological processes and ecosystem services important for both wildlife and human livelihoods (Butchart et al., 2010; DeFries, Hansen, Turner, Reid, & Liu, 2007). A study of the IUCN Red List revealed that 62% of listed species recently studied are endangered by loss of habitat through anthropogenic activities, making habitat loss the number one cause of extinction risk today (Maxwell, Fuller, Brooks, & Watson, 2016).

Establishment of protected areas (PAs) has been a cornerstone in global efforts to reduce loss of wildlife habitat and biodiversity (Cantú-Salazar & Gaston, 2010; Jenkins & Joppa, 2009) with about 15% of the world surface area currently protected (Juffe-Bignoli et al., 2014). However, the long-term viability and sustainability of wildlife populations also depends on the surrounding landscapes outside PAs and

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particularly lesser protected areas (LPAs) for migration between PAs as well as for water and forage (Barr et al., 2011; Craigie et al., 2010; Graham, Douglas-Hamilton, Adams, & Lee, 2009; Hilty, Lidicker, & Merenlender, 2006; Laurance et al., 2006; Rodrigues et al., 2004; Vandermeer & Perfecto, 2007). Variations in resource use among different PA categories and anthropogenic pressures surrounding them threaten the future of both PAs and LPAs (DeFries et al., 2005, 2007).

Tanzania maintains a variety of PA categories which allow different levels of legal restrictions on resource use. These include national parks (NPs) and game reserves (GRs) only allowing photographic tourism and tourist hunting, respectively, some forest reserves permitting selective logging and the Ngorongoro Conservation Area which is similar to NPs but allows cattle grazing by indigenous Maasai pastoralists. The other lower categories of PAs (constituting 18% of the country's land surface) include Game Controlled Areas (GCAs), Wildlife Management Areas (WMAs) and Open Areas (OAs) where extractive resource use such as human settlements and local hunting is permitted under license (MNRT, 2007; Stoner et al., 2007; WWF, 2014). WMAs compose Tanzania's newest protection category that aims to incorporate community efforts to manage wildlife and are increasingly replacing GCAs (Stoner et al., 2007). Limited funding has, however, contributed to minimal law enforcement in many LPAs across the continent making them unable to provide the levels of protection necessary to safeguard conservation of wildlife and their habitat (Caro, 1999; Caro et al., 1998 ; Chase et al., 2016; Lindsey et al., 2014; Nelson, Lindsey, & Balme, 2013; Pelkey, Stoner, & Caro, 2000 ; Pfeifer et al., 2012; Vinya, Syampungani, Kasumu, Monde, & Kasubika, 2011). The concern is that some of these LPAs contain important wildlife populations (Caro, 1999), and their close proximity to fully PAs, such as NPs, helps to facilitate seasonal movements (Caro, Jones, & Davenport, 2009; Jenkins, Corti, Fanning, & Roettcher, 2002) and maintain connectivity between them (Jones, Caro, & Davenport, 2009).

A related problem is the accurate projection and prediction of likely future land conversion and habitat loss. If we can accurately predict where and how much land is likely to be converted in the near future, we can target management to priority areas. Accurate projections of land conversion may provide supporting information on sustainable ecosystem management, e.g. service payments framework for reducing emissions from deforestation and forest cover loss (REDD) programme (Dutschke & Wolf, 2007; Miles & Kapos, 2008). Such programmes are already proposed (and a few implemented, e.g. Khatun et al., 2017) in Tanzania, selling voluntary carbon credits through companies such as Carbon Tanzania (www.carbontazania.com). Modelling the drivers of land-cover change is a challenging undertaking in land-use planning science, and analysis of drivers is a requisite to mitigate and manage the impacts and consequences of change (Turner, 2010). Recent advances in geospatial science have facilitated creation of a diverse set of quantitative and spatial land-cover change models for prospective analysis (Kolb, Mas, & Galicia, 2013). Unfortunately, current projections of future deforestation rely on separate estimation of rates of contagion and probability of conversion, which risks misattribution of true drivers (Rosa, Ahmed, & Ewers, 2014; Rosa, Purves, Carreiras, & Ewers, 2015; Rosa, Purves, Souza, & Ewers, 2013; Soares-Filho et al., 2006; Verburg, Tabeau, & Hatna, 2013), or make simplistic extrapolations of overall rates of change, which ignore the underlying drivers of such changes (Brown, Walker, Manson, & Seto, 2004; Fox, Vogler, Sen, Giambelluca, & Ziegler, 2012; Geostatistics, 2002; Mozumder & Tripathi, 2014; Wu, 1998a; Wu & Webster, 1998b). In addition, land-use model forecasts are not very accurate (Sloan & Pelletier, 2012), and the projections from different models can be highly divergent (Prestele et al., 2016).

Here, we use a recently introduced statistical approach to modelling complex data sets (Illian et al., 2013), namely Integrated Nested Laplace Approximations (INLA) via the R-INLA package (http://www.r-inla.org) to model drivers of habitat conversion from 1972 to 2015 in miombo landscapes as well as estimate the deforestation that could be avoided by creating a new WMA and its benefits for both conservation and human well-being in one of the diminishing wildlife corridors in south-western Tanzania.

2. Materials and methods

2.1. *Study area*

The study area covers about 109,050 km^2 and lies between latitude 6°15′59.38″–8°10′23.78″ S and longitude 30°45′13.29″–35°28′34.44″ E. It comprises the Katavi–Rukwa ecosystem in the west (largely composed of Katavi National Park and Rukwa Game Reserve), a contingent of GRs and GCAs and OAs in the central area and the Ruaha–Rungwa ecosystem (composed of Rungwa, Muhesi and Kisigo Game Reserves and Ruaha National Park) in the east (Figure 1). Areas linking Katavi–Rukwa and Ruaha–Rungwa ecosystems are of particular conservation value as they are thought to join the central, south and western elephant populations and may be one of the largest remaining and most important elephant corridors in East Africa (Jones et al., 2009). Despite this importance, the area has recently been attracting a rapid human population growth (National Bureau of Statistics [NBS], 2012) and there is concern that the ongoing loss of natural habitat linking the two ecosystems will eventually isolate the two ecosystems (Jones et al., 2009). In this analysis, we classified NPs and GRs as fully PAs, GCAs and OAs as LPAs and all other areas in their neighbourhood as unclassified land.

Figure 1. Study area.

2.2. Data sets

2.2.1. Human population

We obtained human population data sets from LandScan, a 30-ac (approximately 1 km) resolution published in July, 2014, the finest resolution global population distribution data available (Bright & Rose, 2014). The LandScan product makes use of national population census data (in Tanzania from the 2012 census – NBS, 2012) and downscales these data based on topography, land cover, road systems and topography, with a correction based on visual comparison of estimates with high-resolution satellite images. Unlike existing national tabular data organized based on political boundaries such as regions, wards and villages, these data sets are spatially explicit (Bright & Rose, 2014). To make future habitat change predictions, we extrapolated the current national human population estimates as provided by LandScan with the current annual average population growth rate of 2.7% (NBS, 2012).

2.2.2. Land use

Land-use maps for the study area were obtained from the Tanzania Wildlife Research Institute spatial database at a spatial resolution of 30 m and subsequently aggregated to ~1 km to match the rest of the data set. They included all categories of PAs that exist within the study.

2.2.3. Roads

Roads for the study area (scale: 1:100,000) were clipped from the existing multipurpose Africover Database for the Environmental Resources produced by the Food and Agriculture Organization of the United Nations (Di Gregorio, 2005). These layers were produced from visual interpretation of digitally enhanced LANDSAT TM images (Bands 4, 3, 2) acquired in 1997. Distance maps where calculated in R (R Core Team, 2016) for distances to both major and minor roads. We assumed that main roads that connect the area to the rest parts of the country would have more impact compared to minor roads, and for this reason, we arbitrarily assigned a weight of half for minor roads relative to the main road. There is evidence to suggest that roads not only promote development (Taylor & Goldingay, 2010; Van Dijck, 2013) but also increase access to those with shortages of arable land elsewhere.

2.2.4. Slope

A Digital Elevation Model (DEM) was obtained from the NASA Shuttle Radar Topographic Mission (SRTM) with a resolution of 1 ac (nominally 30 m, SRTM-1) (NASA, 2013). A slope map was calculated from the DEM using the terrain function in R (R Core Team, 2016) and then aggregated to 1 km resolution to match the rest of the data sets.

2.2.5. Land-cover and accuracy assessment

Details of historical (1972 and 1990) and current (2015) land-cover maps used for this analysis are provided in our recent work (Lobora et al., in press). The overall accuracy assessment and Kappa coefficients for the 2015 final land-cover map at 30 m resolution were 89% and 87%, respectively, suggesting correct assignment of individual classes during classification. For the current analyses, we aggregated the 30-m resolution data to 990 m cells (c. 1 km) and estimated the percentage of land in each classification within the pixel. We used R (R Core Team, 2016) to obtain change maps between 1972 and 1990, 1990 and 2015 as well as the overall 1972 and 2015 for use in the subsequent analysis, based on all classes describing natural habitat during earlier time periods, but which converted to crop fields by the second period.

2.3. *Modelling approach*

2.3.1. *Conceptual overview*

We assumed that the important land-cover change for our purposes was conversions of land from natural or semi-natural land-use types into human-dominated land classes. Each pixel in the analysis represented the percentage of land (itself estimated from a 30-m resolution land classification map) that changed from a semi-natural to human-dominated land category between 1972 and 2015. For each pixel, we had details of the starting percentage cover of different land categories and all other covariates. We assumed that patterns of land-use change would be spatially autocorrelated above and beyond the simple covariate relationships: such contagious land-cover change is typical of human development processes (Dimobe et al., 2015; Ouedraogo et al., 2010; Wittemyer, Elsen, Bean, Burton, & Brashares, 2008) and we used spatial regression methods to incorporate such spatial dependency (Beale, Baker, Brewer, & Lennon, 2013). To validate the model, we used 70% of the data during modelling and used the model to predict percentage change in the remaining 30%. To make predictions into the future, we first made assumptions about human population density growth and then predicted our model assuming similar contagious effects continue and relationships between covariates and land-cover change remain similar. Full details are presented below.

2.3.2. *Model implementation*

Our Bayesian model estimation employed the recently proposed INLA for latent Gaussian models, a fast approach to fitting a wide variety of statistical models (Martino & Rue, 2010; Rue, Martino, & Chopin, 2009). The models approximate the posterior distribution with high accuracy and much faster than Markov Chain Monte Carlo making them suitable for a wide range of applications and have recently been employed in a variety of ecological contexts (Cosandey-Godin, Krainski, Worm, & Flemming, 2014; Illian et al., 2013; Illian, Sørbye, Rue, & Hendrichsen, 2012; McCarthy, 2007). Rue et al. (2009) provide a detailed description of the methodology and we used R-INLA (Riebler, 2013) to fit models in R v 3.3.0 (R Core Team, 2016). Furthermore, we used INLA to fit spatially explicit intrinsic Conditional Autoregressive Models (iCAR), a class of spatial models that have demonstrated to perform well under a variety of real-world conditions (Beale, Brewer, & Lennon, 2014). Using such a hierarchical model allows us to simultaneously model the contagious effect of land conversion (through the iCAR component), and the primary spatial drivers (through the fixed effects). Essentially, INLA allows fitting of complex spatial regression models that provide the flexibility and spatial contagion effects required for modelling land-use change in a computational efficient manner.

We imported all covariates, including distance to the nearest road, land cover in 1972, land-use designation (statutory designation), human population and DEM to R (R Core Team, 2016) as raster objects within the raster package (Hijmans & Van Etten, 2012). Where necessary, we reprojected all surfaces to the same resolution (990 m) and projection (WGS84). We computed the proportion of land within each pixel that originally were not crops but later converted to crops. To estimate the human footprint of each cell, we combined estimated population density with distance to the road network (specifically, we divided the population in each cell by the distance to the nearest road). We combined all layers to a single spatial data set, including the change maps for 1972, 1990 and 2015, slope, altitude, land use and human footprint. NPs and GRs were excluded from the analysis since human activities are prohibited within their boundaries, in contrast to GCAs and OAs. We also excluded lakes within the study area boundary for the same reasons. Finally, we scaled numerical values to mean 0 and standard deviation of 1 for all covariates, identified neighbours within 1.75 km (i.e. queen's case adjacency) and fitted the model.

2.3.3. *Model evaluation and future predictions*

To evaluate the model, we used a simple pseudo-R^2 statistic consisting of the Spearman's rank correlation between predictions generated from models fitted using 70% of the data with the remaining 30% of observed values. The test aimed to quantify the discrepancy between observed and the expected values within our model.

To obtain predicted change estimates for the next 20 years, we created a new human population data set assuming an average growth rate of 2.7 over the next 20 years reflecting 'business as usual' (NBS, 2012) and increased accessibility to the area following the planned surfacing of main roads in the area. Prediction for these new values in INLA simply required refitting the model with both original data and the new data as additional rows for which land-use change were missing.

To estimate land-cover change that would be prevented from change in the next 20 years (2015–2035) following the establishment of a functional WMA, we used the output from the predicted future change within this area and assumed that the successful creation of the WMA would halt all land conversion (ignoring the possibility of recovery in some already degraded areas). This allowed us to compute the area of expected land conversion within the proposed WMA and we combined this area with estimates of carbon storage capacity of miombo woodland at 13–30 t/ha (Munishi, Mringi, Shirima, & Linda, 2010; Ryan, Williams, & Grace, 2011; Shirima et al., 2011) to generate a first estimate of CO_2 emissions that could be prevented through protection of the land. We carried out modelling and analyses using the R 3.3.0 software (R Development Core Team, 2016) as detailed in Supplementary Appendix.

3. Results

3.1. *Land-cover change model validation*

Our model validation showed a strong correlation between predicted and observed change, with R^2 of 0.85 (N = 17,359, $p < 0.001$; Figure 3(c)).

3.2. *Variability in habitat losses in different land uses in the study area from 1972 to 2035*

Unsurprisingly, our study reveals that land use has a strong impact on probability of habitat conversion. Within the unclassified land-use type, open woodlands had the highest probabilities of habitat conversion to croplands between 1972 and 2015 (0.404; 95% CI = [0.399, 0.411]). This particular land-use type comprises land with unrestricted human use and it is where the vast majority of the human population is located within the study area. Between OAs and GCAs, which were of key interest to this study, the former had the highest probability of land conversion to croplands (0.221; 95% CI = [0.198, 0.223]) compared to the latter (0.00017; 95% CI = [0.512, 0.00017]). When we looked at the probabilities for change only within OAs where fastest conversions are taking place, we found that Bushland had the highest probability overall (0.403; 95% CI = [0.357, 0.450]) followed by closed woodland (0.242; 95% CI = [0.233, 0.251]) and open woodland (0.210; 95% CI = [0.198, 0.223]). Wetlands had the least probability for conversion overall (0.089; 95% CI = [0.073, 0.108]).

3.3. *Detecting drivers of change*

Our analysis revealed the human footprint index, a combination of human population density and road network, as a leading driver of habitat conversion, with more conversion observed in areas with a high human population and road network and vice versa (Figure 2(a)). Such impacts were slightly moderated by a shallow negative correlation with slope, where conversions are lowest in areas of steeper slopes (Figure 2(b)).

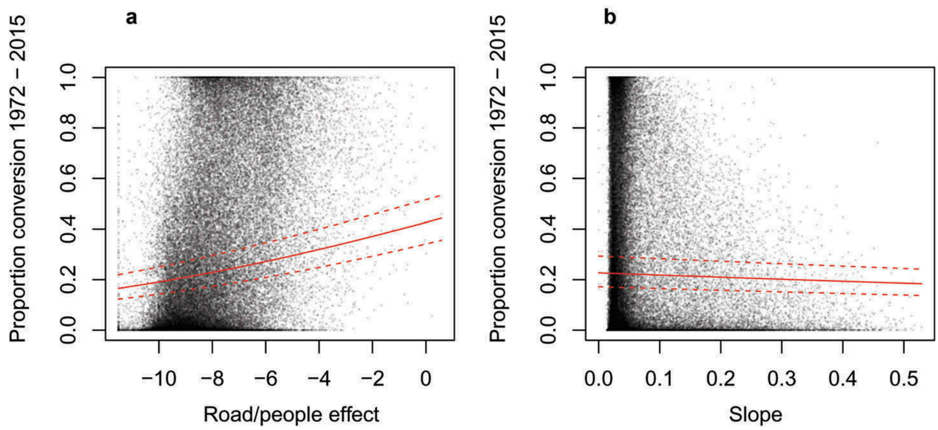

Figure 2. Human footprint and slope effects on habitat change in the study area. (a) Positive correlation for the combined human population density and road network on habitat conversion from 1972 to 2035. (b) Slope (in radians) showing a negative correlation on habitat conversion suggesting conversions be lowest on steeper slopes within both GCAs and OAs in the study area.

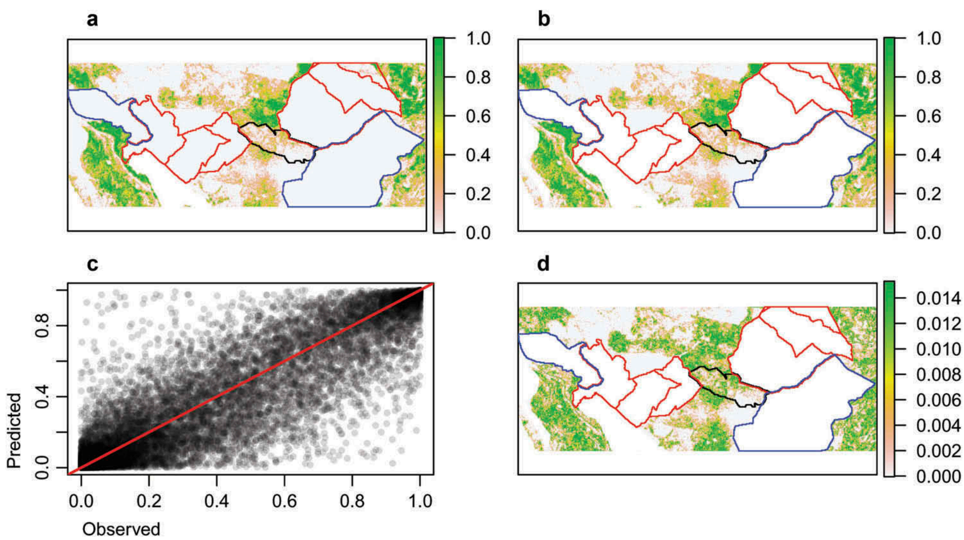

Figure 3. Predicted habitat change in the study area due to the human footprint. (a) Observed proportion habitat change between 1972 and 2015, (b) predicted habitat change from 1972 to 2015 from the INLA model, (c) validation plot showing correlation between observed and fitted values in 30% of validation cells not used for model building and (d) predicted future habitat change from 2015 to 2035 assuming an average human population density growth rate of 2.7% annually over that period (NBS, 2012) over the next 20 years and reduced effective distance to roads (index of accessibility) across the board assuming increased accessibility following proposed tarmac by 1 standard deviation. Black polygon shows change within the proposed WMA linking Katavi–Rukwa and Ruaha–Rungwa ecosystems, red represents Game Reserves and blue denotes National Parks. The latter two categories have firm boundaries and hence excluded from the analysis.

3.4. *Habitat loss from 1972 to 2035*

Our model depicts that local deforestation rate is positively linked to distances from roads and human population density (Figure 3). With an estimated increase of human population of 2.7% yearly and development of paved main road network leading to the study area from other parts of the country, both GCAs and OAs are predicted to experience habitat change over the next 20 years as people continue to increase if the status quo continues (Figure 3).

3.5. *Prevented habitat change through a WMA establishment*

We estimated that about 1640 ha of habitat conversion could be halted in the next 20 years by merging Piti East and Rungwa South OA into a WMA (Figure 3(d)). Such prevented loss of natural habitat could result in significant carbon storage benefits. Assuming 13–30 t of carbon storage per ha, which is typical for miombo (Shirima et al., 2011), we estimated that between 21,320 and 49,200 t of carbon emissions could be avoided by designation of the proposed new WMA. Assuming a carbon market price of around $4 per ton (Jenkins, 2014), this could generate between US$ 4264 and 6560 per year or between US$ 85,280 and 131,200 over the next 20 years assuming REDD+ is implemented.

4. Discussion

We found clear correlations between land conversion for agriculture and areas with the highest human footprint (combining population density and accessibility). Official land-use designations have had varied impacts to rates of deforestation such that undesignated areas had high probabilities of conversions, whilst OAs, the lowest protection class, were more vulnerable to land-use change and habitat conversion than GCAs. GCAs and OAs form the largest proportion of PAs network in Tanzania (MNRT, 2007) and their lower protection status makes them more prone to invasion by people for agricultural- and livestock-keeping practices. The vast majority of Tanzania's population live in rural areas and this is where LPAs are located (NBS, 2012) and therefore their long-term survival will depend on the development of a new strategy to prevent the ongoing large-scale land conversion to agriculture in these areas (Caro & Davenport, 2015).

Our analysis indicates the importance of anthropogenic pressure for predictions of habitat loss and consistent with findings by Allen and Barnes (1985) who found a positive correlation between human population density and habitat loss in a wide range of countries in Africa, Latin America and Asia. Recent studies in West Africa by Dimobe et al. (2015) and Ouedraogo et al. (2010) revealed agricultural expansion and human population along roads as main drivers of natural habitat loss, respectively, and this is consistent with the findings from our study. The scale of human settlement around PAs is considered a strong predictor of illegal harvest and species extinction within PAs (Brashares, Arcese, & Sam, 2001; Karanth, Curran, & Reuning-Scherer, 2006) as well as high deforestation rates and disturbance (Markovchick-Nicholls et al., 2008). Wittemyer et al. (2008) examined such impacts directly by comparing human population growth rates in PA buffers in habitat surrounding 55 forest PAs in Africa and Latin America and found the rates of deforestation to be highest around PAs where human population was greatest, suggesting that settlements around PAs isolate PAs from the surrounding landscape through the creation of a ring of disturbance, islands, making wildlife and especially large migratory mammals such as African elephants more vulnerable to extinction.

Habitat loss through deforestation typically follows road network development, particularly in land uses with minimum or no protection (Adeney, Christensen, & Pimm, 2009; Barber, Cochrane, Souza, & Laurance, 2014; Blake et al., 2007; Laurance, Goosem, & Laurance, 2009; Stoner et al., 2007; Van Dijck, 2013). Our results confirm the patterns from elsewhere in Africa (Mertens & Lambin, 2000), Latin America (Mas et al., 2004) and Southeast Asia (Clements et al., 2014) that roads are one of the major drivers of deforestation due to increased access. Roads in forested areas increase deforestation because forest loss is revealed to be spatially highly contagious (Boakes, Mace, McGowan, & Fuller, 2010; Clements et al., 2014). A recent study conducted by Hidalgo and Muñoz (2014) indicates that about 25 million kilometres of new paved roads will be developed across the globe by mid-century, sufficient to encircle the Earth more than 600 times (Laurance et al., 2015). This is a matter of great concern since nine-tenths of these roads are projected to be in developing nations which sustain most of the planet's biologically rich and environmentally important ecosystems (Hidalgo & Muñoz, 2014; Laurance et al., 2015). Our results show how roads that penetrate into wilderness areas can have serious effects through increased accessibility to natural resources (Figure 2(a)).

We projected persistent future losses over the next 20 years assuming business as usual. The unclassified land-use type where most hamlets are situated will continue to transition into urban centres since this is already a human-dominated land use with little or no chance for restoration. Protecting the last remaining *last of the wild* potential for providing potential connectivity through a WMA establishment could be the best way forward in an effort to avoiding frictions between managers and communities which could lead to poor support of local communities to conservation as highlighted elsewhere in the country (Holmern, Mkama, Muya, & Røskaft, 2006) and across the continent (Karidozo, 2007; Mbaiwa, 2005; Weladji & Tchamba, 2003). The key underlying assumption of the WMA concept is decentralization of resource ownership to local communities with the expectation that they will in turn attach value to wildlife as they do for other forms of land use such as agriculture (URT, 1998; Wilfred, 2010). Preservation of the remaining habitat in both Piti and Rungwa OAs whilst providing for communities is paramount to ensuring long-term conservation for the remnant habitat potential to link Katavi–Rukwa and Ruaha–Rungwa ecosystems in south-western Tanzania providing the longest remaining wildlife corridor in East Africa.

Estimating the amount of deforestation that could be avoided by effectively protecting areas (development of a baseline or benchmark) has been a key challenge to the establishment of REDD+ schemes (Gibbs, Brown, Niles, & Foley, 2007; Olander, Gibbs, Steininger, Swenson, & Murray, 2008; Pfaff, Robalino, Lima, Sandoval, & Herrera, 2014). REDD+ requires an assessment of baseline current levels of habitat conversion and the future trajectories of loss to be estimated (Brown et al., 2007). Our assessment shows that if a WMA is set-up, 1640 ha of key natural habitat would be protected, wildlife movement patterns would continue with all the advantages that brings and between $85,280 and $131,200 could be made from selling carbon credits over the next 20 years assuming a REDD+ programme is implemented. Such approaches can work in Tanzania as demonstrated by the initial successes of a REDD+ project not far from the study area in south-west Tanzania (Khatun et al., 2017). If the status quo prevails, a critical habitat connecting two important African elephant populations would be lost.

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