land

MDPI

Article

Rapid Appraisal of Wildlife Corridor Viability with Geospatial Modelling and Field Data: Lessons from Makuyuni, Tanzania

Emmanuel H. Lyimo [1], Gabriel Mayengo [1], Kwaslema M. Hariohay [1], Joseph Holler [2], Alex Kisingo [1], David J. Castico [3], Niwaeli E. Kimambo [2,*], Justin Lucas [2], Emanuel H. Martin [1] and Damian Nguma [4]

[1] College of African Wildlife Management, Mweka, Moshi P.O. Box 3031, Tanzania; emmanuel.lyimo@mwekawildlife.ac.tz (E.H.L.); gabriel.mayengo@mwekawildlife.ac.tz (G.M.); kwaslema.hariohay@mwekawildlife.ac.tz (K.M.H.); alex.kisingo@mwekawildlife.ac.tz (A.K.); emagingi@gmail.com (E.H.M.)
[2] Department of Geography, Middlebury College, McCardell Bicentennial Hall, 287 Bicentennial Way, Middlebury, VT 05753, USA; josephh@middlebury.edu (J.H.); jtlucas@middlebury.edu (J.L.)
[3] Tanzania People and Wildlife, Arusha P.O. Box 11306, Tanzania; dcastico@tanzaniapeoplewildlife.org
[4] Tanzania Wildlife Research Institute, Arusha P.O. Box 661, Tanzania
* Correspondence: nkimambo@middlebury.edu; Tel.: +1-802-443-5143

Abstract: Connectivity between protected areas is necessary to prevent habitat fragmentation. Biodiverse countries like Tanzania craft legislation to promote habitat connectivity via the creation of ecological corridors, but their viability for wildlife often remains unknown. We therefore develop a scalable and replicable approach to assess and monitor multispecies corridor viability using geospatial modeling and field data. We apply and test the approach in the Makuyuni study area: an unprotected ecological corridor connecting Tarangire National Park to Essmingor mountain, Makuyuni Wildlife Park and Mto Wa Mbu Game Controlled Area. We analyzed the viability of Makuyuni as an ecological corridor by creating and validating a geospatial least-cost corridor model with field observations of wildlife and livestock. We created the model from publicly available spatial datasets augmented with manual digitization of pastoral homesteads (*bomas*). The least-cost corridor model identified two likely pathways for wildlife, confirmed and validated with field observations. Locations with low least-cost values were significantly correlated with more wildlife observations (Spearman's rho = −0.448, p = 0.002). Our findings suggest that Makuyuni is a viable ecological corridor threatened by development and land use change. Our methodology presents a replicable approach for both monitoring Makuyuni and assessing corridor viability more generally. The incorporation of manually digitized homesteads (*bomas*) and field-based livestock observations makes corridor assessment more robust by taking into account pastoral land uses that are often missing in land cover maps. Integration of geospatial analysis and field observations is key for the robust identification of corridors for habitat connectivity.

Keywords: landscape connectivity; least-cost corridor model; line transect sampling; corridor assessment; wildlife management; validation

check for updates

Citation: Lyimo, E.H.; Mayengo, G.; Hariohay, K.M.; Holler, J.; Kisingo, A.; Castico, D.J.; Kimambo, N.E.; Lucas, J.; Martin, E.H.; Nguma, D. Rapid Appraisal of Wildlife Corridor Viability with Geospatial Modelling and Field Data: Lessons from Makuyuni, Tanzania. *Land* **2024**, *13*, 1647. https://doi.org/10.3390/land13101647

Academic Editor: Shiliang Liu

Received: 8 August 2024
Revised: 2 October 2024
Accepted: 7 October 2024
Published: 9 October 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Promoting connectivity between isolated protected areas is necessary to counter the negative impacts of habitat fragmentation and isolation [1–3]. Field projects and legislation are underway globally to create ecological corridors: some simply to facilitate wildlife movement and others to provide habitat [4]. There is special urgency for such efforts in areas with high biodiversity and increasing human pressure like the savanna ecosystems in Tanzania that support numerous endangered and endemic species. Tanzania has protected 36% of its land [5]; however, the majority of corridors linking the protected areas are at risk of disappearing due to factors such as agricultural expansion, land use change, road development, and natural resource extraction [6].

Ecological corridor viability may be assessed with local expert knowledge, wildlife observation, and geospatial least-cost corridor models [7,8]. Interviews with local experts can reveal where wildlife tends to move between protected areas and provide a relatively cheap method for tracking actual utilization of wildlife corridors [9]. However, these qualitative data typically lack systematic sampling and precision [8]. Aerial surveys, transect surveys, or tracking can provide robust observation of wildlife movement and corridor use [10]. Tracking with collars is expensive and challenging to perform at scale [11], while surveys are limited to a "moment in time" when the survey is performed [12].

Researchers may model the viability of a wildlife corridor by analyzing how environmental variables hinder or permit fauna movement [8,13]. Spatial modeling that utilizes satellite-derived environmental data can be cheaply and quickly deployed and is gaining popularity in landscape ecology [9]. Environmental variables include land use (e.g., agriculture, grazing lands, protected areas) and land cover (e.g., shrubland, buildings, roads) [14]. Variable effects on wildlife movement may be determined by expert knowledge, field observations, or modeling habitat with secondary species-presence data [15,16].

Anthropogenic land uses tend to impede wildlife movement but are often misclassified or missing from land cover maps and geospatial databases of savanna landscapes [8]. Homesteads constructed from natural building materials are challenging to detect from satellite imagery using automated methods for classifying land cover or detecting objects because they are not spectrally distinct from the surrounding landscape [17]. Grasslands and fallow cropland are often misclassified [8]. Livestock and grazing areas can be transient and invisible in a land cover map, but livestock can affect herbivorous wildlife distribution through diseases and the consumption of large amounts of available biomass and the resulting displacement of wildlife from competitive pressures [18,19]. Livestock are often concentrated near pastoral homesteads, which may lead wildlife to avoid the settled areas and exhibit antipredator behavior [20]. Without additional field observations, models would overestimate potential connectivity and ecological corridor viability [21].

Geospatial least-cost corridor models should be validated prior to application in conservation management, but connectivity validation is surprisingly under-practiced [16]. Validation requires knowledge of how flora and fauna use the supposed corridor or connectivity site [21,22]. Interviews with local experts and residents can conveniently provide qualitative validation, but robust and representative quantitative validation requires field observations with systematic sampling [8,22]. Our goal in this paper is to showcase the integration of a geospatial least-cost corridor model with field observations to assess and validate the viability of an ecological corridor [23,24]. We focus on Makuyuni, a potential ecological corridor in the threatened and biodiverse Tarangire–Manyara ecosystem of northern Tanzania [25].

Tanzania is in the top-ten list of countries with most species on the IUCN Red List (1121 species [26]). Tanzania has placed 36% of its land under some form of conservation [5], but the protected areas are not optimally connected. Connectivity is crucial given the habitat requirements of over 340 species of large mammals found in the protected areas [27]. These habitat requirements are significant due to high densities of tertiary consumers such as lions, especially in the Mara–Serengeti ecosystem [28–30], and large movements of ungulates, such as the great wildebeest migration of 1.3 million individuals [31].

Wildlife corridors are necessary to counter habitat fragmentation in Tanzania, but the corridor viability in the context of land use change is often unknown [32,33]. Corridors are particularly important in large, protected complexes with strong seasonal variations where wildlife survival is reliant on broad-scale movement between large conservation areas. Corridors that facilitate these broad-scale movements have higher conservation value, particularly if they are also utilized by endangered species [34]. The Tarangire–Manyara ecosystem supports a large population of herbivores and carnivores that need to migrate seasonally [35]. A 2017 assessment of Tanzanian corridors highlighted that only two out of ten historical corridors remain in the ecosystem: Kwakuchinja, connecting Tarangire National Park with Lake Manyara National Park, and Makuyuni, connecting

Tarangire with Essmingor mountain [27]. For this reason, Makuyuni is in Tanzania's top five priority connectivity sites [27] but its viability as a corridor remains unknown. A repeatable baseline assessment of the corridor viability and human and wildlife utilization is essential for informing policy and management [27,36].

In this paper, we assess the Makuyuni area for viability as an ecological corridor. We generate a multispecies least-cost corridor model and validate it with field observations of wildlife and livestock. We use the term "wildlife" to refer to a list of encountered mammal species (See Appendix A, Table A1) and for consistency with the terminology of "wildlife corridor analysis" in geospatial modelling and acknowledge that our usage excludes other species. We augment the modeling process with field observations and high-resolution satellite image interpretation to better represent anthropogenic land use in a savannah landscape. While we demonstrate an efficient approach to replicable ecological corridor viability assessment, we also caution against using secondary data to model ecological corridors without validation.

2. Materials and Methods

To assess the viability of Makuyuni as a wildlife corridor, we (1) acquired and created geospatial data to model a least-cost corridor, mapping areas of least resistance to wildlife movements, and (2) validated the least-cost corridor model with field-based wildlife and livestock observation data. All data files and procedures for this study are available in the OSF archive at [37].

2.1. Study Area

Our study area is Makuyuni (Figure 1), a historic ecological corridor connecting Tarangire National Park to the Monduli dispersal area approximately 15 km north and the Essmingor Nature Forest Reserve approximately 25 km north [7]. In addition to Tarangire National Park, Makuyuni is bordered by Manyara Ranch and three major game controlled areas: Simanjiro, Lolkisale, and Mto wa Mbu (Figure 1). Management authorities vary by area and include the national park authority, the forest services agency, the wildlife management agency with local communities (for game controlled areas), and the African Wildlife Foundation with local communities (for Manyara Ranch) [38,39]. The viability and sustainability of Makuyuni as an ecological corridor is uncertain in a region with many different conservation authorities and without formal conservation management for the corridor itself [40].

There is substantial human presence in the Makuyuni area, particularly in the Naitolia, Makuyuni, and Lolkisale villages [7]. The Maasai, Barbaig, Iraq, and Mbugwe groups also inhabit low-density settlements around the villages [41]. Major livelihood activities include domestic animal keeping, subsistence and commercial agriculture, mining, and tourism [40]. We delineated the study area boundary based on expert knowledge and an aerial wildlife survey conducted in the Tarangire–Manyara ecosystem during the 2016 dry season [42].

2.2. Data Sources

2.2.1. Data for Least-Cost Corridor Model

To model a least-cost corridor (Figure 2), we collated geospatial data on land use and land cover, buildings, settlements, and roads (Table 1 and Figure 3). We selected land use and land cover data that represent human activity relevant to wildlife distribution and movement and used it to calculate a cost surface.

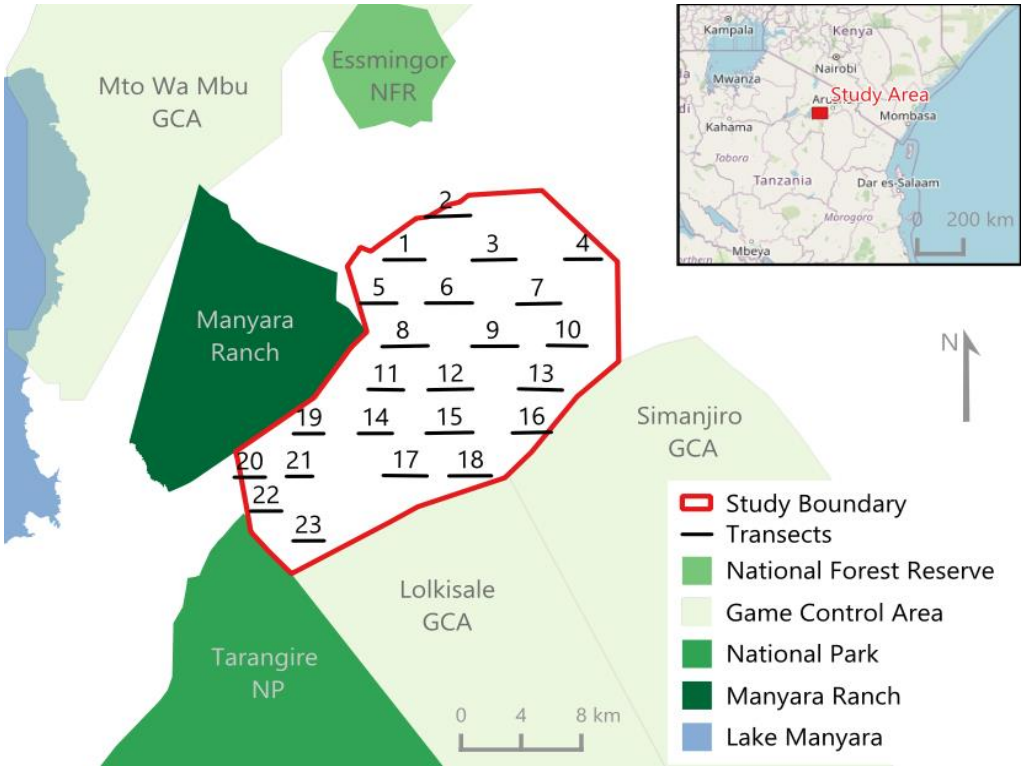

Figure 1. Makuyuni study site, survey transects (lines numbered with transect ID), and nearby conservation areas [43].

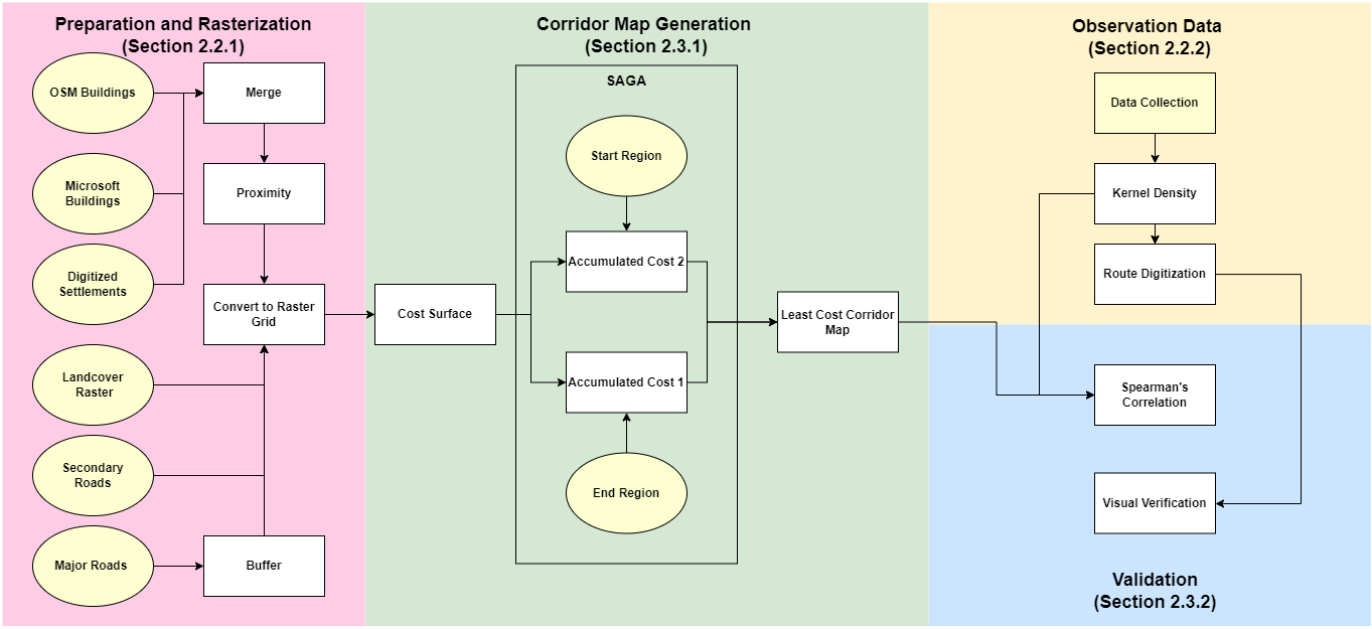

Figure 2. Conceptual workflow for least-cost corridor model and validation. Sections 2.2.1, 2.2.2, 2.3.1 and 2.3.2.

Table 1. Table of least-cost corridor model inputs.

Input	Weight	Cost Values	Data Sources	Citation
Land use and land cover (LULC)	1	Developed = 1 Cropland = 0.75 Bare land = 0.1 Grassland = 0.25 Water = 0.15 Wetland = 0.15 Woodland = 0.01 Shrubland = 0.01 data	[44]	[8,19,45,46]
Settlements/building footprints (Ss)	1	Proximity (m): 0–1 = 1 1–50 = 0.8 50–100 = 0.6 100–150 = 0.4 150–200 = 0.2 200+ = 0	Manual digitization/[43,47]	[19,48–51]
Major roads (MRs)	0.75	Presence = 1 Absence = 0	[43]	[14,45,52]
Secondary roads (SRs)	0.75	Presence = 1 Absence = 0	[43]	[45,53]

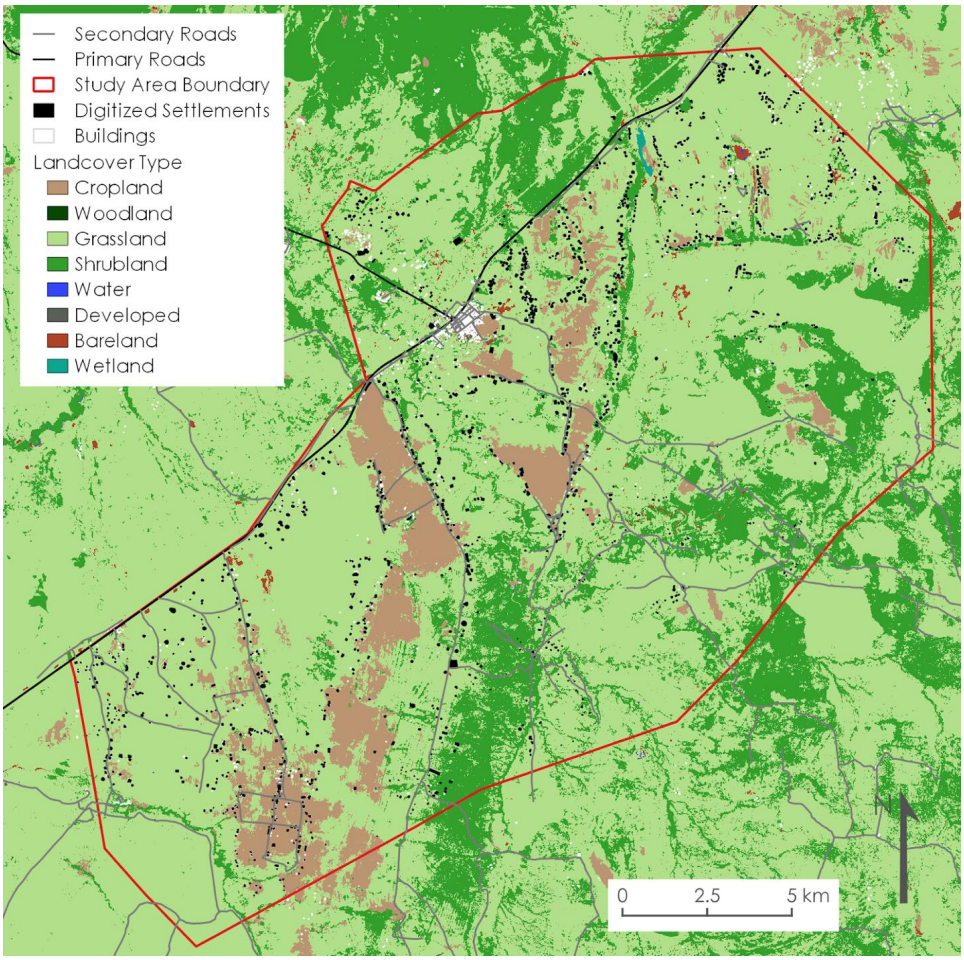

Figure 3. Map of the Makuyuni study area showing inputs for the least-cost corridor model, as listed in Table 1.

Buildings

We obtained building outlines from Microsoft Building Footprints [47] and OpenStreetMap [43]. The Microsoft database was created using convolutional neural networks for machine learning [54] with high-resolution remote sensing data provided by Maxar. The OpenStreetMap database was created mainly by volunteer humanitarian mappers working remotely by interpreting satellite images [55]. We compared the data to satellite image basemaps and found it unreliable for pastoral Maasai homesteads called *bomas*, consisting of multiple buildings enclosed by a fence. Since *bomas* are constructed of natural materials, they cause errors of omission in algorithmic approaches to building detection [17].

We therefore manually digitized the enclosure area of each *boma*. We digitized 1525 total *bomas* from 7 July to 10 July 2023 using QGIS and the Google satellite basemap. A total of 700 of the *bomas* (45.9%) contained at least one building captured by either OpenStreetMap or the Microsoft database, while 481 *bomas* (31.5%) were missed by both databases. Our database is therefore more complete and also represents the full extent of *bomas*, rather than standalone buildings.

Land Cover Map

We used a recent high-resolution and high-accuracy land cover dataset to distinguish land cover types of importance to wildlife corridors including cropland, forest/dense trees (woodland), grassland, shrubland, water, built-up areas, wetland, and bare land [44]. The woodlands are dominated by woody species like *Vachellia tortilis*, *Vachellia xanthophloea*, *Terminallia brownii*, and *Makhamia zanzibarica*. Grasslands are dominated by herbaceous species like *Sporobolis pyramidalis*, *Eragrotis superba Cynodon dactyalon*, and *Hyparrnia rufa.* Shrublands are dominated by semi-woody species like *Flueggea virosa*, *Salvadora persica*, and *Solunum incanum* (see Appendix A, Figure A2 for illustrative images). The land cover dataset was created with U-Net deep learning architecture using Sentinel-1 radar timeseries and 3.7 m resolution PlanetScope tropical basemaps from 2017 to 2018 [44]. The resulting land cover map had an overall accuracy of 83.57%, and 90% for cropland/urban built-up areas. The map had the most confusion between forest and shrubland and between shrubland and grassland [44]. We considered the errors and accuracy acceptable for our analysis, as the confused land cover classes had similar model weights (Table 1).

Roads

Roads influence wildlife movement, so we incorporated them into the model (Table 1). We queried OpenStreetMap features on 6 and 7 July 2023 [43] using the QuickOSM plugin. We defined major roads as features, with "route" as the key and "road" as the value, capturing highways B144 and A104. We defined secondary roads as features, with "surface" as the key and "unpaved" as the value, or with "highway" as the key and "track" and "unclassified" as the values.

2.2.2. Data from Field-Based Observations

We generated 23 east–west line transects spaced approximately 3 km apart across the study area with a stratified sample [56,57]. We used Google Earth satellite imagery and ground observations to verify that transects covered all shrubland, grassland, and woodland habitats in the study site [58]. Transects extended into a buffer zone surrounding the study area to counter edge effects [57,59]. Some transects were necessarily adjusted to avoid rivers and gorges.

Transect surveys took place on foot on 18 to 30 May 2021 and 30 September to 15 October 2021. The two times of the surveys spanned the wet (February–May) and the dry (August to November) seasons. We walked along the 3 km transect until a mammal was sighted then recorded the GPS coordinates, weather conditions, habitat type, perpendicular distance of the sighting from the transect line, type of species, and number of individuals sighted. The GPS coordinates were recorded using a Garmin map 64s GPS (Olathe, KS, USA), observations were carried out through Olympus 20 × 50 binoculars

(Tokyo, Japan), and distances were recorded using a Tesco VOLT 600, NORM 900 m, or KA 800 m Golf rangefinder (Erie, PA, USA). Though surveys were conducted in the wet and dry seasons to account for wildlife's seasonal behaviors and movement patterns; the majority of the observations occurred during the wet season, as this is when most hooved wildlife disperse into the study area [60]. At each transect, we summarized the number of wildlife or livestock encounters(e) and the total count of individuals(c) for each species.

2.3. Analysis

To model a least-cost corridor (where a corridor is a sum of multiple least-cost paths), we first created a cost surface map representing the suitability of the landscape for multispecies wildlife movement based on land cover, buildings, and roads. To validate the modeled least-cost corridor, we checked the corridor against field observations of wildlife presence in the study area via visual and statistical analysis. We assessed the corridor viability by interpreting the model and field observation findings.

2.3.1. Least-Cost Corridor Model Creation

We used the QGIS version 3.16.7 graphical modeler (see Appendix A, Figure A1) to model least-cost corridors using factors influencing wildlife movement as inputs [61]. Each input layer for the model was transformed into a 10 m raster grid, and the units were normalized to range from 0 to 1 (lowest to highest movement cost, respectively).

We reclassified each land cover type into a movement cost value based on the authors' expert knowledge and published literature. We assigned low-cost values to shrubland and woodland, as these land cover types contain more natural features that facilitate wildlife movement [45]. Grasslands had higher cost value to account for the field-reported substantial presence of livestock and resulting competitive pressures [18,19]. Water and wetlands have also been shown to have negative correlations with wildlife density in immediate proximity, resulting in their higher cost values [8,45]. Cropland was identified as a high-cost land cover type due to the implied presence of humans and active cultivation [8].

We varied the cost of buildings and *bomas* as a function of proximity. We assigned buildings and *bomas* the highest cost of 1. We reduced the cost by 0.2 at 50 m increments until reaching the minimum cost of 0 at a distance of 200 m or more from a building or settlement. Though some studies suggest that buildings may impede wildlife movement at distances greater than 200 m, we used 200 m as a cut-off point due to the multispecies focus of our model [49,51].

We represented the influence of roads on wildlife movement with the highest cost of 1. We included a 300 m buffer around major roads to account for a zone of influence of roads on wildlife movement [45].

To create a cost surface, we combined all the cost layers (land use and land cover (*LULC*), settlements/building footprints (*S*s), major roads (*MR*s), and secondary roads (*SR*s)) for each location in the study area with a simple weighted sum using the following equation:

$$Movement\ Cost = LULC + S + 0.75 * MR + 0.25 * SR \quad (1)$$

The model weights and cost values are relative (e.g., a major road hinders wildlife movement more than a secondary road). LULC and Ss were assigned overall weights of 1 due to their importance, as they can either strongly limit or facilitate wildlife movement [46]. MRs were assigned a high weight due to the substantial effects they have on wildlife movement, particularly on large mammals [14,45,52]. SRs were assigned a lower weight of 0.25, as they posed a lesser potential impact on wildlife movements since many of the secondary roads and tracks identified in the study area are unpaved and crossed by wildlife [45,53]. Given the assigned weights, the maximum cost value attainable at a location was 3 and the minimum cost value attainable was 0 (no cost).

To generate a map of areas with high connectivity, we used the cost surface to calculate the accumulated cost of movement from a start region on the southern side of Makuyuni to the end region in the north implemented in SAGA software version 7.8.2. The start

and end regions were placed several kilometers away from the border of the study area to minimize edge effects, and they extended the full width of the study area to theoretically allow wildlife to start at any point along the southern edge and end at any point along the northern edge. The total least cost of each location was calculated as the sum of the accumulated cost to reach the southern start region and the accumulated cost to reach the northern end region from that location. A least-cost path forms where pixels with low least-cost values connect the start and end zones. A modeled least-cost corridor is a region composed of multiple least-cost paths and is the most ideal route for wildlife movement.

2.3.2. Least-Cost Corridor Model Validation

We validated the modeled least-cost corridor with two approaches: visual validation and statistical correlation. For visual validation, we digitized an "observed corridor" using kernel density maps generated from field data and compared those to the modeled least-cost corridor. For statistical correlation, we used Spearman's rank to test for a statistical association between the modeled least-cost corridor and observed wildlife counts.

We mapped wildlife observation counts and livestock observation counts with kernel density using Gaussian distributions and 300 m radii, resulting in 10 m resolution heatmaps. We digitized two observed wildlife corridors by encircling areas with relatively high wildlife density, representing our visual interpretation of wildlife corridor viability based solely on field data observations.

We tested correlation between the modeled least-cost corridor and field-based wildlife observations using line transects as a sampling unit. We used zonal statistics to calculate the minimum least-cost value for each transect. We tested for a statistical correlation between the minimum least-cost value and the total amount of wildlife observed at that transect with a one-tailed Spearman's rank [21]. Our null hypothesis was, "There is no correlation between the minimum least-cost value and the amount of wildlife at the transect," and our alternative hypothesis was, "There is an inverse correlation between the minimum least-cost value and the amount of wildlife at the transect." In other words, we expect to find less wildlife in locations modeled as having higher movement cost, and more wildlife in locations modeled as having lower movement cost.

2.3.3. Do Livestock Affect Wildlife Corridor Use?

To analyze the effect of pastoral activities and livestock movement on wildlife, we recorded livestock presence (encounters(e) and the total count of individuals(c) for each species) during field surveys. We used R software v 4.4.1 [62] to perform a statistical test called the one-tailed Spearman's rank to check for a correlation between the total amount of livestock and the total amount of wildlife in each transect with >0 observations. Our null hypothesis was, "There is no correlation between the amount of livestock and the amount of wildlife observed in a transect." Our alternative hypothesis was, "There is an inverse correlation between the amount of livestock and the amount of wildlife observed in a transect."

3. Results

3.1. Least-Cost Corridor Model

Our modeling identified two distinct regions that delineate potential wildlife corridors (Figure 4) that measure approximately 7000 ha each. As expected, we found that locations dominated by factors with higher resistance for wildlife movement (e.g., settlements and roads) resulted in high-cost areas. Locations dominated by factors with lower resistance for movement (e.g., shrubland and woodland) resulted in lower-cost areas and potential corridors. Essentially, clusters of settlements created barriers where no least-cost path could form, while connected shrubland and woodland areas formed least-cost paths.

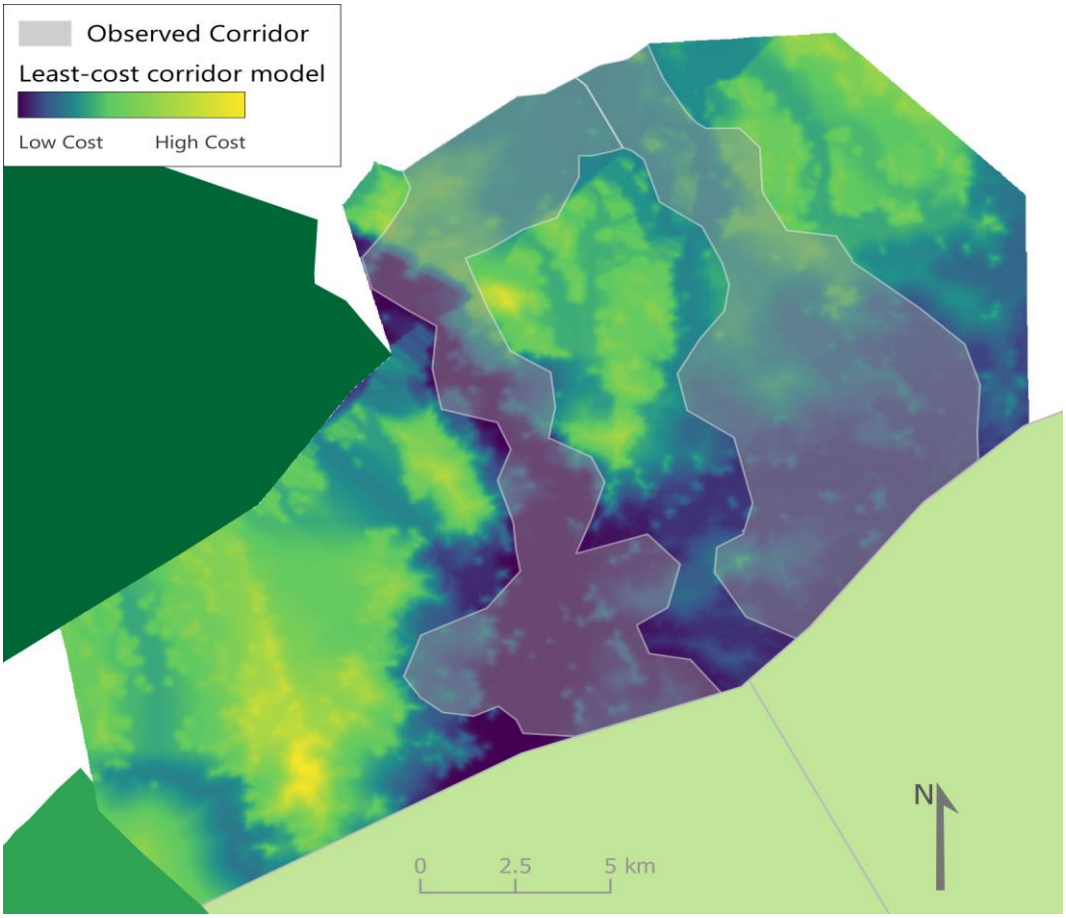

Figure 4. Modeled least-cost corridors that are locations with low cost of movement (blue) relative to the rest of the study area. Overlaid are "observed corridors," generated by digitizing regions with high wildlife counts in field surveys. The most western "observed corridor" measures 7065 ha, while the most eastern one measures 7552 ha.

The north/south alignment of the modeled least-cost corridor was strongly influenced by the location of buildings, including the digitized Maasai settlements (*bomas*). The digitized settlements (*bomas*) formed distinct linear patterns (Figure 3) that created high-cost barriers in the east/west direction. Thus, the presence of closely spaced buildings and settlements created higher-resistance hotspots in the model. The resulting corridor is therefore shaped by human land use patterns that prevent east/west movement. Woodlands and shrubland land cover dominated locations identified as potential corridors (Figure 4). In other words, locations identified as least cost had more to do with the absence of other human uses like settlements and roads.

3.2. Least-Cost Corridor Model Validation Using Field-Based Data

3.2.1. Field-Based Wildlife and Livestock Encounters

We observed 10 different wildlife species during field sampling sessions. Based on the number of encounters (e) and the total count of individuals across all encounters (c), the most abundant species was the Thomson gazelle (e = 17; c = 88), followed by elephants (e = 25; c = 88), zebras (e = 14; c = 147), and giraffes (e = 10; c = 30) (Appendix A, Table A1). The least observed wildlife were dik-diks, grant gazelle, impala, jackals, and wildebeest. We also observed hyena signs (scats; e = 5). We observed wildlife in 65.2% of transects, with the highest concentration in transects 13, 18, 10, 7, 1, and 16 (Figure 5). Wildlife observations differed strongly by land cover type: Woodlands were the most diverse land cover, followed by bare land and grassland (Simpson's Diversity Index: woodland: 0.8, bare land: 0.6, shrubland: 0.5; see Appendix A, Table A3).

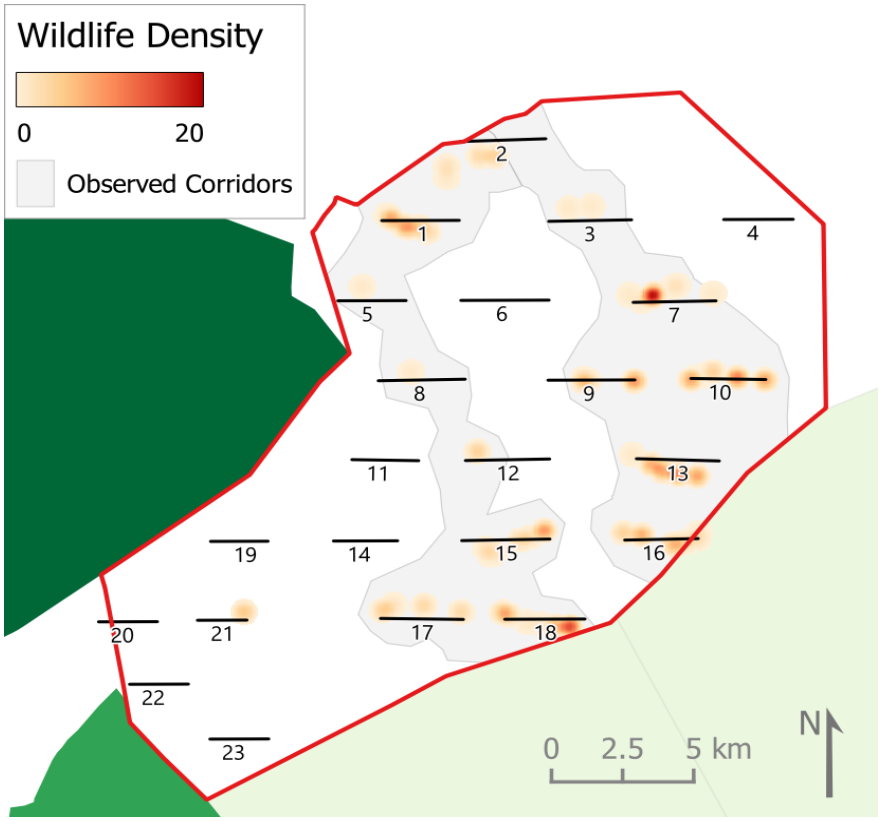

Figure 5. Wildlife density based on total count of individuals of all wildlife species encountered during the field transect survey (kernel diameter = 300 m). Numbered lines indicate survey transects.

3.2.2. Visual Validation of Modeled Least-Cost Corridor with Kernel Density Analysis

Kernel density mapping of the wildlife showed uneven distribution, with the highest wildlife concentrations on transects 13, 18, 10, and 7 (Figure 5). This distribution suggests two potential regions that are in higher utilization by wildlife, for which we generated bounding polygons (Figure 4). The observed corridor based on transect surveys corresponded to modeled least-cost corridors generated without knowledge of wildlife movement (Figure 4). Visually, there is strong correspondence between the least-cost corridors generated from geospatial modeling and regions of high wildlife concentration outlined from field data. Essentially, the modeled least-cost corridor correctly identified potential wildlife corridors.

3.2.3. Least-Cost Corridor Model Validation with Statistical Analysis

We found a statistically significant relationship between the minimum least-cost value of a transect and the total amount of wildlife observed at that transect (n = 23 transects, Spearman's rho = -0.448, p = 0.002). Thus, we rejected the null hypothesis that "there is no correlation between the minimum least-cost value and the amount of wildlife at the transect." Essentially, the least-cost path model correctly identifies locations ideal for wildlife movement, and wildlife concentration in those locations corroborates the corridor viability.

3.2.4. Wildlife Avoiding Livestock

We observed four livestock species during field surveys: sheep, goats, cattle, and donkeys (Appendix A, Table A2). Livestock were present in 73.9% of the transects, although the density varied (Figure 6). We observed the highest concentration of livestock on transects 6, 3, 13, 11, and 1.

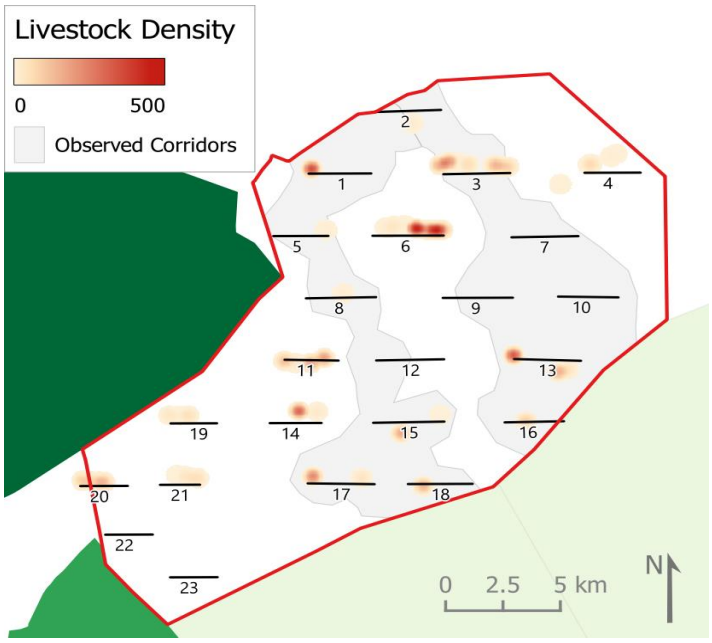

Figure 6. Livestock density based on total count of individual livestock (sheep, goats, cows, donkeys) encountered during the field transect survey (kernel diameter = 300 m). Numbered lines indicate survey transects.

Locations with high livestock concentrations tended to be clustered near *bomas* and had lower wildlife concentrations. We found an inverse relationship between the number of livestock and the number of wildlife provided the transect had at least one observation ($n = 21$, Spearman's rank rho = -0.239, $p = 0.149$. The inverse correlation was not statistically significant. However, two transects (1 and 13) ranked in the top five for both livestock and wildlife.

4. Discussion

Our study demonstrated the utility of geospatial least-cost corridor modeling for wildlife corridor identification in pastoral landscapes. We paired geospatial modeling with field-based observations, and both showed similar potential wildlife corridors. Our geospatial approach was uniquely effective because it revealed human land uses like pastoral *bomas* that are often hard to capture in both geospatial models and field-based observations [63]. Our effort to digitize *bomas* revealed previously undetected linear patterns of development along roads and footpaths (Figure 3) that proved to be significant barriers to wildlife movement. Analysis of field-based observations that incorporated livestock observations further allowed for more robust corridor evaluation. Consideration of pastoral settlements constructed from natural materials (*bomas*) and livestock strongly explained observed patterns of wildlife movements. We recommend that pastoral land uses be considered in geospatial and field-based analysis of corridor viability, and our study demonstrates how.

Our study found that the settlement patterns of pastoralist *bomas* strongly constrained the layout of corridors. The *bomas* constrained the loci of connected natural habitats into a north/south direction and could completely block potential corridors if the *bomas* were to expand. The western corridor through Makuyuni is at greatest risk and already appears to have evidence of wildlife conflict with humans and livestock. Landscape ecology fundamentally recognizes the importance of the arrangement of habitat as a key factor for creating connectivity [64], but this aspect is often overlooked when setting aside wildlife corridors. The spatial arrangement of the pastoralist *bomas*, however, also presents an opportunity for land use planning to increase connectivity. For example, allowing gaps in the settlements may significantly increase connectivity without the need, necessarily,

to clear the site of settlement/human use. The spatial arrangement of land use should be strongly considered instead of clearing corridors of human land use, as the corridor legislation proposes [39].

4.1. Least-Cost Corridor Modeling vs. Field Observations for Wildlife Corridor Analysis

4.1.1. Least-Cost Corridor Modeling

Our least-cost corridor modeling identified potential paths for wildlife movement in the study area with a purely geospatial approach. This methodology can be replicated in other similar study sites whose corridor viability needs to be assessed, particularly in Tanzania. Legislation for wildlife corridors is a big step towards protecting biodiversity, but to ensure functional connectivity, there need to be effective and repeatable site-specific assessments of the connectivity sites [27]. Our geospatial modeling approach provides a robust and replicable analytical framework that can be rapidly deployed to assess a connectivity site.

Since the corridor delineation relies on the identification of least-cost values and thresholds set by the analyst, the area cited represents a cost threshold. In other words, conservation planners should focus on the variables important to wildlife movement rather than the exact hectares identified as low cost.

A geospatial modeling approach can further guide connectivity management decisions by identifying land use priorities. For example, the eastern least-cost corridor had higher cost values, likely due to the density of settlements and anthropogenic land use near highway A104. Spatial continuity is important for habitat quality and connectivity; thus, the direction of expansion of future settlements could further reduce connectivity [50]. Thus, to minimize habitat fragmentation, it may help to pay attention to the direction of grazing, cultivation, and settlement pressures in a potential corridor site [27,53,65].

Our geospatial modeling approach requires manual generation of input data for landscape features that cannot be automatically detected via artificial intelligence algorithms. Still, we found that datasets generated by volunteer mappers and/or artificial intelligence missed a significant portion of settlements that are built using natural materials. Some analysts have deployed extremely customized algorithms for the extraction of *bomas*, but their approach can be technologically prohibitive and require custom software and expertise [17]. Our approach of manually digitizing the *bomas* using open-source software and datasets can be easily replicated in analogous landscapes and significantly improve modeling of landscape connectivity at a relatively low cost.

Generally, least-cost corridor modeling involves subjective decision-making in determining the appropriate spatial data and weights to include. To ensure sound modeling and robust findings, the spatial data selection should involve robust literature and on-the-ground knowledge (see Table 1). Furthermore, the model needs to be validated with field data, a surprisingly limited practice in connectivity modeling [16]. Our analytical approach from model creation to validation demonstrates an easily replicable approach for evaluating connectivity in analogous habitats.

Connectivity modeling needs to be cognizant of target species. Our model needed to account for the habitat needs of many species. In fact, we used the term "wildlife," with our field data being based on observed large mammal species in the study area (see Appendix A, Tables A1 and A3). While other studies account for multispecies needs by modeling individual species separately then averaging the models [66], our approach chose reasonable parameters for all concerned species at the outset. This made sense, as we could assume similar habitat needs of target species. In general, areas with intact habitat such as grassland, shrubland, and woodland are more useful to savannah wildlife and thus make for more viable corridor locations [46,49]. This finding makes sense based on our field observations, as we saw the highest diversity in woodlands, which is a more intact habitat. Conversely, areas with more human land use, such as settlement, present a hindrance to wildlife use [49].

4.1.2. Field-Based Observations for Corridor Analysis

We validated the modeled least-cost corridor using field-based wildlife observations and found a statistically significant correlation between modeled least-cost corridors and wildlife presence, providing confidence that the modeled corridors are in fact viable ecological corridors. The western modeled least-cost corridor was a wider band of low cost and more connected than the eastern one, but wildlife observations were more concentrated on the latter. The western modeled least-cost corridor had higher livestock counts and was surrounded by *bomas*, suggesting competition from human land use. Furthermore, wildlife moves around, and thus, a moment-in-time observation may not fully reveal presence or absence. This uncertainty could be reduced with GPS tracking or wildlife camera data.

Pastoral features like grazing areas, rest areas, transhumance routes, and watering areas can seem ephemeral and therefore challenging to incorporate into geospatial analysis [63]. Nevertheless, our analysis included field-based livestock observations. Our general finding was that a high concentration of livestock is inversely correlated to wildlife concentration, though the correlation was not statistically significant. The inverse relationship, however, indicated that livestock and wildlife may be competing for resources, and in some areas livestock presence may displace wildlife [18,19].

5. Conclusions

We developed a replicable geospatial approach for assessing corridor viability and for monitoring the Makuyuni corridor site. We accounted for hard-to-capture pastoral land uses by manually digitizing homesteads (*bomas*) and collecting field-based livestock observations. The integration of geospatial analysis and field observations is key for the robust identification of corridors for habitat connectivity. We showed that Makuyuni has two important wildlife pathways. The spatial arrangement of the pastoralist *bomas* and other settlements presents an opportunity for land use planning to increase connectivity. For example, allowing gaps in the settlements may significantly increase connectivity of the Makuyuni area and its utility as a corridor without necessarily needing to clear the corridor of settlements/human use.

Author Contributions: Conceptualization, E.H.L., J.H., G.M., N.E.K. and J.L.; methodology, E.H.L., J.H., N.E.K. and J.L.; software, J.H. and J.L.; validation, E.H.L., J.H., J.L., A.K. and E.H.M.; formal analysis, E.H.L. and J.L.; investigation, E.H.L., G.M., K.M.H., J.L., D.J.C. and D.N.; data curation, E.H.L., J.L. and D.N.; writing—original draft preparation, E.H.L., K.M.H., J.H., N.E.K., A.K., J.L., D.J.C., and E.H.M.; writing—review and editing, E.H.L., J.H., N.E.K. and J.L.; visualization, E.H.L., J.H. and J.L.; supervision, J.H. and N.E.K.; project administration, G.M., J.H., N.E.K., A.K. and E.H.M.; funding acquisition, G.M., J.H., N.E.K., A.K. and E.H.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the College of African Wildlife Management, Mweka grant number Folio No. 11, and Middlebury's Undergraduate Research Program. The APC was funded by the C.V. Starr International Fellowship at Middlebury College.

Data Availability Statement: The original data presented in the study are openly available on OSF with the digital object identifier (DOI) doi:10.17605/OSF.IO/8KHDX [37].

Acknowledgments: We thank Alana Lutz and Andy Atallah for creating R scripts to reproduce the cost surface [67]. We thank two anonymous reviewers for their constructive feedback. The research followed all due protocol for research as outlined by the Tanzania Commission for Science and Technology (COSTECH), permit No. 2022-874-NA-2022-0301.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

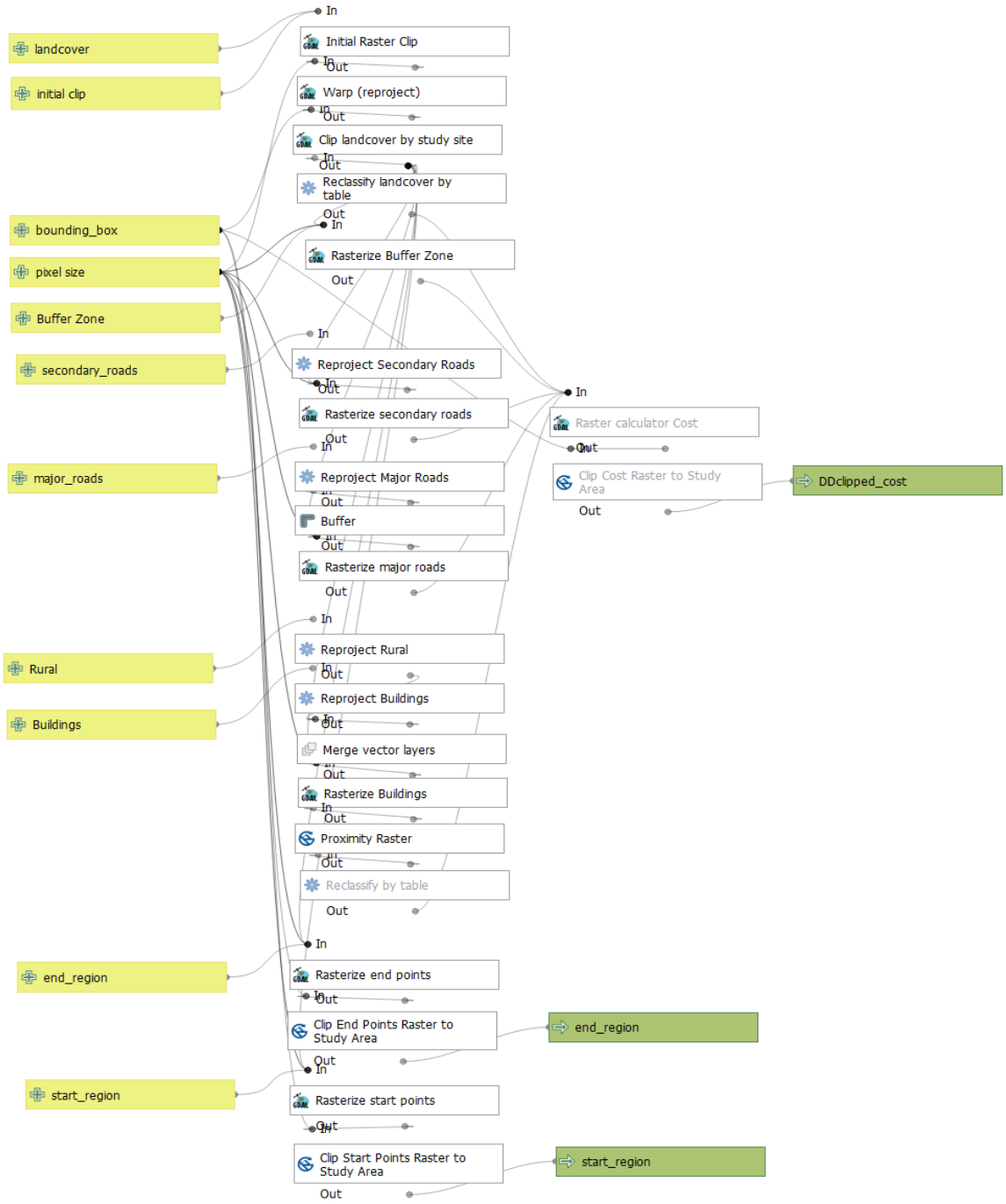

Figure A1. QGIS graphic model for the least-cost wildlife corridor analysis.

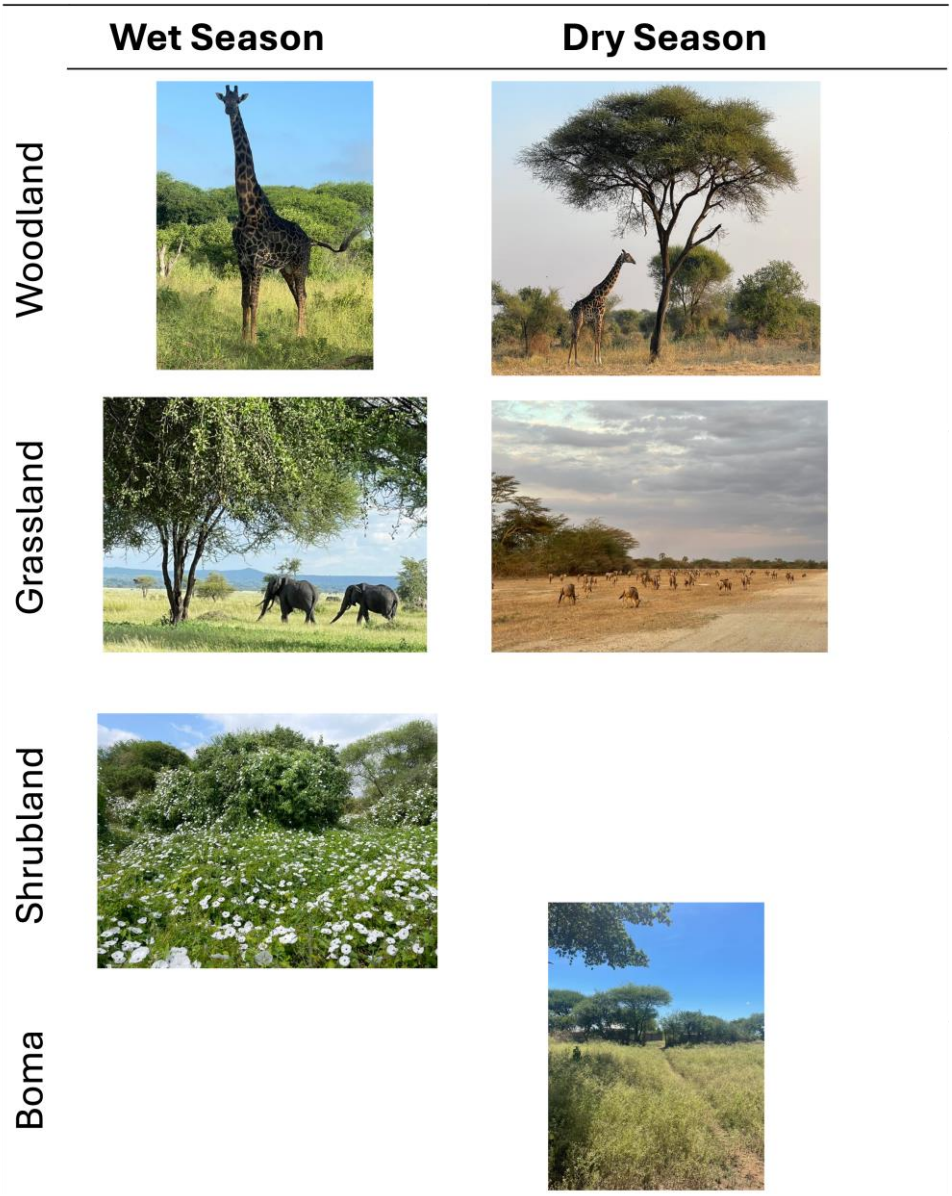

Figure A2. Sample land cover types across the Tarangire–Manyara ecosystem. Photographs are illustrative of flora and fauna of the ecosystem and do not all originate from the Makuyuni study area. Credit: Salum Mpapa.

Table A1. Observation data of wildlife collected during field sampling (wet and dry seasons).

Species	Encounter	Counts	Habitat
Elephant	25	87	Woodland
Thomson gazelle	17	88	Grassland
Zebra	14	147	Woodland, grassland
Giraffe	10	30	Woodland
Jackal	7	7	Woodland
Hyena	5	Scat	Woodland, grassland
Dik-dik	5	6	Woodland, shrubland
Grant's gazelle	4	21	Grassland
Impala	1	4	Woodland
Wildebeest	1	2	Grassland

Table A2. Observation data of livestock collected during field sampling.

Species	Encounters	Counts
Sheep and goat	44	3417
Cattle	32	1300
Donkey	4	23

Table A3. Comparative diversity of different land cover types in the study area (wet season).

Species Name	Bare Land	Shrubland	Woodland	Grassland	Counts
Dik-dik	1	1	4	NA	6
Elephant	0	0	77	NA	77
Grant's gazelle	0	0	21	NA	21
Giraffe	0	3	18	NA	21
Hyena	0	0	4	NA	4
Impala	1	0	2	NA	3
Jackal	0	0	7	NA	7
Thomson's gazelle	0	0	34	NA	34
Zebra	4	0	63	NA	67
Species count	3	2	9	NA	9
Simpson's Diversity Index	0.6	0.5	0.8	NA	NA
Cattle	NA	190	118	992	1300
Donkey	NA	11	3	9	23
Sheep and goat	NA	371	1546	1500	3417

References

1. Fischer, J.; Lindenmayer, D.B. Landscape Modification and Habitat Fragmentation: A Synthesis. *Glob. Ecol. Biogeogr.* **2007**, *16*, 265–280. [CrossRef]
2. Margules, C.R.; Pressey, R.L. Systematic Conservation Planning. *Nature* **2000**, *405*, 243–253. [CrossRef] [PubMed]
3. Silveira, L.; Sollmann, R.; Jácomo, A.; Diniz-Filho, J.A.; Torres, N. The Potential for Large-Scale Wildlife Corridors between Protected Areas in Brazil Using the Jaguar as a Model Species. *Landsc. Ecol.* **2014**, *29*, 1213–1223. [CrossRef]
4. Hilty, J.; Lidicker, W.; Merenlender, A. *Corridor Ecology: The Science and Practice of Linking Landscapes for Biodiversity Conservation*; Island Press: Washington, DC, USA, 2006.
5. Gizachew, B.; Rizzi, J.; Shirima, D.D.; Zahabu, E. Deforestation and Connectivity among Protected Areas of Tanzania. *Forests* **2020**, *11*, 170. [CrossRef]
6. Jones, T.; Caro, T.; Davenport, T.R.B. *Wildlife Corridors in Tanzania*; TAWIRI: Arusha, Tanzania, 2009; p. 60.
7. Caro, T.; Jones, T.; Davenport, T.R.B. Realities of Documenting Wildlife Corridors in Tropical Countries. *Biol. Conserv.* **2009**, *142*, 2807–2811. [CrossRef]
8. Riggio, J.; Caro, T. Structural Connectivity at a National Scale: Wildlife Corridors in Tanzania. *PLoS ONE* **2017**, *12*, e01874072017. [CrossRef] [PubMed]
9. Goldman, M. Constructing Connectivity: Conservation Corridors and Conservation Politics in East African Rangelands. *Ann. Assoc. Am. Geogr.* **2009**, *99*, 335–359. [CrossRef]
10. Graham, M.D.; Douglas-Hamilton, I.; Adams, W.M.; Lee, P.C. The Movement of African Elephants in a Human-Dominated Land-Use Mosaic. *Anim. Conserv.* **2009**, *12*, 445–455. [CrossRef]
11. Bond, M.L.; Bradley, C.M.; Kiffner, C.; Morrison, T.A.; Lee, D.E. A Multi-Method Approach to Delineate and Validate Migratory Corridors. *Landsc. Ecol.* **2017**, *32*, 1705–1721. [CrossRef]
12. Marshall, A.R.; Lovett, J.C.; White, P.C.L. Selection of Line-Transect Methods for Estimating the Density of Group-Living Animals: Lessons from the Primates. *Am. J. Primatol.* **2008**, *70*, 452–462. [CrossRef]
13. Cisneros-Araujo, P.; Ramirez-Lopez, M.; Juffe-Bignoli, D.; Fensholt, R.; Muro, J.; Mateo-Sánchez, M.C.; Burgess, N.D. Remote Sensing of Wildlife Connectivity Networks and Priority Locations for Conservation in the Southern Agricultural Growth Corridor (SAGCOT) in Tanzania. *Remote Sens. Ecol. Conserv.* **2021**, *7*, 430–444. [CrossRef]
14. Xu, J.; Wang, J.; Xiong, N.; Chen, Y.; Sun, L.; Wang, Y.; An, L. Analysis of Ecological Blockage Pattern in Beijing Important Ecological Function Area, China. *Remote Sens.* **2022**, *14*, 1151. [CrossRef]
15. Weber, T.; Sloan, A.; Wolf, J. Maryland's Green Infrastructure Assessment: Development of a Comprehensive Approach to Land Conservation. *Landsc. Urban Plan.* **2006**, *77*, 94–110. [CrossRef]
16. Lalechère, E.; Bergès, L. A Validation Procedure for Ecological Corridor Locations. *Land* **2021**, *10*, 1320. [CrossRef]
17. Cheng, K.; Popescu, I.; Sheets, L.; Scott, G.J. Analysis of Deep Learning Techniques for Maasai Boma Mapping in Tanzania. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2022**, *15*, 3916–3924. [CrossRef]

18. Gordon, I.J. Review: Livestock Production Increasingly Influences Wildlife across the Globe. *Animal* **2018**, *12*, s372–s382. [CrossRef]
19. Ogutu, J.O.; Owen-Smith, N.; Hans-Peter, P.; Said, M.Y.; Kifugo, S.C.; Reid, R.S.; Gichohi, H.; Kahumbu, P.; Andanje, S. Changing Wildlife Populations in Nairobi National Park and Adjoining Athi-Kaputiei Plains: Collapse of the Migratory Wildebeest. *Open Conserv. Biol. J.* **2013**, *7*, 11–26. [CrossRef]
20. Duporge, I.; Finerty, G.E.; Ihwagi, F.; Lee, S.; Wathika, J.; Wu, Z.; Macdonald, D.W.; Wang, T. A Satellite Perspective on the Movement Decisions of African Elephants in Relation to Nomadic Pastoralists. *Remote Sens. Ecol. Conserv.* **2022**, *8*, 841–854. [CrossRef]
21. Laliberté, J.; St-Laurent, M.-H. Validation of Functional Connectivity Modeling: The Achilles' Heel of Landscape Connectivity Mapping. *Landsc. Urban Plan.* **2020**, *202*, 103878. [CrossRef]
22. Gracanin, A.; Mikac, K.M. Evaluating Modelled Wildlife Corridors for the Movement of Multiple Arboreal Species in a Fragmented Landscape. *Landsc. Ecol.* **2023**, *38*, 1321–1337. [CrossRef]
23. Ayebare, S.; Ponce-Reyes, R.; Segan, D.; Watson, J.; Possingham, H.; Seimon, A.; Plumptre, A. Identifying Climate-Resilient Corridors for Conservation in the Albertine Rift. 2013. Available online: https://www.researchgate.net/publication/264676660_Identifying_climate-resilient_corridors_for_conservation_in_the_Albertine_Rift_Acknowledgements?channel=doi&linkId=53eb290b0cf2fb1b9b6af37b&showFulltext=true (accessed on 7 August 2024).
24. Moilanen, A.; Wilson, K.A.; Possingham, H. (Eds.) *Spatial Conservation Prioritization: Quantitative Methods and Computational Tools*; Oxford University Press: Oxford, UK; New York, NY, USA, 2009; ISBN 978-0-19-954777-7.
25. Cincotta, R.P.; Wisnewski, J.; Engelman, R. Human Population in the Biodiversity Hotspots. *Nature* **2000**, *404*, 990–992. [CrossRef] [PubMed]
26. WCS Tanzania Program Species. Available online: https://tanzania.wcs.org/Species.aspx (accessed on 30 January 2024).
27. Minitstry of Natural Resources and Tourism. *Tanzania Wildlife Corridor Assessment, Prioritization, and Action Plan*; Ministry of Natural Resources and Tourism: Dodoma, Tanzania, 2022; p. 155.
28. Cusack, J.J.; Swanson, A.; Coulson, T.; Packer, C.; Carbone, C.; Dickman, A.J.; Kosmala, M.; Lintott, C.; Rowcliffe, J.M. Applying a Random Encounter Model to Estimate Lion Density from Camera Traps in Serengeti National Park, Tanzania. *J. Wildl. Manag.* **2015**, *79*, 1014–1021. [CrossRef] [PubMed]
29. Durant, S.M.; Craft, M.E.; Hilborn, R.; Bashir, S.; Hando, J.; Thomas, L. Long-Term Trends in Carnivore Abundance Using Distance Sampling in Serengeti National Park, Tanzania. *J. Appl. Ecol.* **2011**, *48*, 1490–1500. [CrossRef]
30. Hardouin, M.; Searle, C.E.; Strampelli, P.; Smit, J.; Dickman, A.; Lobora, A.L.; Rowcliffe, J.M. Density Responses of Lesser-Studied Carnivores to Habitat and Management Strategies in Southern Tanzania's Ruaha-Rungwa Landscape. *PLoS ONE* **2021**, *16*, e0242293. [CrossRef]
31. Serneels, S.; Lambin, E.F. Impact of Land-Use Changes on the Wildebeest Migration in the Northern Part of the Serengeti–Mara Ecosystem. *J. Biogeogr.* **2001**, *28*, 391–407. [CrossRef]
32. Dickman, A.J. Complexities of Conflict: The Importance of Considering Social Factors for Effectively Resolving Human–Wildlife Conflict. *Anim. Conserv.* **2010**, *13*, 458–466. [CrossRef]
33. Rimaze, D.; Machumu, A.; Mremi, R.; Eustace, A. Diversity and Abundance of Wild Mammals between Different Accommodation Facilities in the Kwakuchinja Wildlife Corridor, Tanzania. *Sci. Afr.* **2020**, *9*, e00480. [CrossRef]
34. Newmark, W.D. The Role and Design of Wildlife Corridors with Examples from Tanzania. *Ambio* **1993**, *22*, 500–504.
35. Morrison, T.A.; Bolger, D.T. Connectivity and Bottlenecks in a Migratory Wildebeest Connochaetes Taurinus Population. *Oryx* **2014**, *48*, 613–621. [CrossRef]
36. Clark, S.G.; Hohl, A.M.; Picard, C.H.; Thomas, E. (Eds.) *Large-Scale Conservation in the Common Interest*; Springer Series on Environmental Management; Springer International Publishing: Cham, Switzerland, 2015; ISBN 978-3-319-07418-4.
37. Lyimo, E.; Lucas, J.; Kimambo, N.; Holler, J. *Rapid Appraisal of Wildlife Corridor Viability with Geospatial Modelling and Field Data: Lessons from Makuyuni, Tanzania*; COS: Charlottesville, VA, USA, 2024. [CrossRef]
38. Caro, T.; Davenport, T.R.B. Wildlife and wildlife management in Tanzania. *Conserv. Biol.* **2016**, *30*, 716–723. [CrossRef]
39. Goldman, M. Strangers in Their Own Land: Maasai and Wildlife Conservation in Northern Tanzania. *Conserv. Soc.* **2011**, *9*, 65–79. [CrossRef]
40. Kiffner, C.; Lee, D.; Bond, M. *Tarangire: Human-Wildlife Coexistence in a Fragmented Ecosystem*; Springer: Berlin, Germany, 2022; ISBN 978-3-030-93606-8.
41. Debonnet, G.; Nindi, S. Technical Study on Land Use and Tenure Options and Status of Wildlife Corridors in Tanzania. USAID 2017. Available online: https://conservationcorridor.org/cpb/Debonnet_and_Nindi_2017.pdf (accessed on 30 January 2024).
42. Tanzania Wildlife Research Institute Aerial Census in Tarangire-Manyara Ecosystem, Tanzania. 2016. Available online: https://www.honeyguide.org/wp-content/uploads/2020/04/TAWIRI_Tarangire-Manyara-Ecosystem-Census-Report-2016_Final.pdf (accessed on 30 January 2024).
43. OpenStreetMap Contributors. OpenStreetMap 2023. Available online: https://www.openstreetmap.org/ (accessed on 10 July 2023).
44. Song, L.; Estes, A.B.; Estes, L.D. A Super-Ensemble Approach to Map Land Cover Types with High Resolution over Data-Sparse African Savanna Landscapes. *Int. J. Appl. Earth Obs. Geoinf.* **2023**, *116*, 103152. [CrossRef]
45. Gunda, D.M.; Chambi, D.; Eustace, A. Do Vegetation, Disturbances, and Water Influence Large Mammal Distribution? *Geol. Ecol. Landsc.* **2022**, *6*, 150–158. [CrossRef]

46. Said, M.Y.; Ogutu, J.O.; Kifugo, S.C.; Makui, O.; Reid, R.S.; De Leeuw, J. Effects of Extreme Land Fragmentation on Wildlife and Livestock Population Abundance and Distribution. *J. Nat. Conserv.* **2016**, *34*, 151–164. [CrossRef]
47. Microsoft. Open Dataset of Machine Extracted Buildings in Uganda and Tanzania. 2019. Available online: https://github.com/microsoft/Uganda-Tanzania-Building-Footprints (accessed on 7 August 2024).
48. Gangadharan, A.; Vaidyanathan, S.; St. Clair, C.C. Planning Connectivity at Multiple Scales for Large Mammals in a Human-Dominated Biodiversity Hotspot. *J. Nat. Conserv.* **2017**, *36*, 38–47. [CrossRef]
49. Mworia, J.K.; Kinyamario, J.I.; Githaiga, J.M. Influence of Cultivation, Settlements and Water Sources on Wildlife Distribution and Habitat Selection in South-East Kajiado, Kenya. *Environ. Conserv.* **2008**, *35*, 117–124. [CrossRef]
50. Owen-Smith, N.; Hopcraft, G.; Morrison, T.; Chamaillé-Jammes, S.; Hetem, R.; Bennitt, E.; Van Langevelde, F. Movement Ecology of Large Herbivores in African Savannas: Current Knowledge and Gaps. *Mammal Rev.* **2020**, *50*, 252–266. [CrossRef]
51. Polfus, J.L.; Hebblewhite, M.; Heinemeyer, K. Identifying Indirect Habitat Loss and Avoidance of Human Infrastructure by Northern Mountain Woodland Caribou. *Biol. Conserv.* **2011**, *144*, 2637–2646. [CrossRef]
52. Bowman, J.; Ray, J.C.; Magoun, A.J.; Johnson, D.S.; Dawson, F.N. Roads, Logging, and the Large-Mammal Community of an Eastern Canadian Boreal Forest. *Can. J. Zool.* **2010**, *88*, 454–467. [CrossRef]
53. Fyumagwa, R.; Gereta, E.; Hassan, S.; Kideghesho, J.R.; Kohi, E.M.; Keyyu, J.; Magige, F.; Mfunda, I.M.; Mwakatobe, A.; Ntalwila, J.; et al. Roads as a Threat to the Serengeti Ecosystem. *Conserv. Biol.* **2013**, *27*, 1122–1125. [CrossRef]
54. Tan, M.; Le, Q.V. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. *arXiv* **2020**, arXiv:1905.11946.
55. Herfort, B.; Lautenbach, S.; Porto De Albuquerque, J.; Anderson, J.; Zipf, A. The Evolution of Humanitarian Mapping within the OpenStreetMap Community. *Sci. Rep.* **2021**, *11*, 3037. [CrossRef] [PubMed]
56. Buckland, S.; Anderson, D.; Burnham, K.; Laake, J.; Borchers, D.; Thomas, L. *Introduction to Distance Sampling: Estimating Abundance of Biological Populations*; Oxford University Press: Oxford, UK, 2001; Volume xv, ISBN 978-0-19-850649-2.
57. Thomas, L.; Buckland, S.T.; Rexstad, E.A.; Laake, J.L.; Strindberg, S.; Hedley, S.L.; Bishop, J.R.B.; Marques, T.A.; Burnham, K.P. Distance Software: Design and Analysis of Distance Sampling Surveys for Estimating Population Size. *J. Appl. Ecol.* **2010**, *47*, 5–14. [CrossRef]
58. Andries, A.; Murphy, R.J.; Morse, S.; Lynch, J. Earth Observation for Monitoring, Reporting, and Verification within Environmental Land Management Policy. *Sustainability* **2021**, *13*, 9105. [CrossRef]
59. Strindberg, S.; Buckland, S.T. Zigzag Survey Designs in Line Transect Sampling. *J. Agric. Biol. Environ. Stat.* **2004**, *9*, 443–461. [CrossRef]
60. Kahurananga, J.; Silkiluwasha, F. The Migration of Zebra and Wildebeest between Tarangire National Park and Simanjiro Plains, Northern Tanzania, in 1972 and Recent Trends. *Afr. J. Ecol.* **2003**, *35*, 179–185. [CrossRef]
61. Theobald, D.M. A Note on Creating Robust Resistance Surfaces for Computing Functional Landscape Connectivity. *Ecol. Soc.* **2005**, *10*, r1. [CrossRef]
62. R Core Team. *R: A Language and Environment for Statistical Computing*; R Core Team: Vienna, Austria, 2024.
63. Turner, M.; Mcpeak, J.; Gillin, K.; Kitchell, E.; Kimambo, N. Reconciling Flexibility and Tenure Security for Pastoral Resources: The Geography of Transhumance Networks in Eastern Senegal. *Hum. Ecol.* **2016**, *44*, 199–215. [CrossRef]
64. Turner, M.G. Landscape Ecology: The Effect of Pattern on Process. *Annu. Rev. Ecol. Syst.* **1989**, *20*, 171–197. [CrossRef]
65. Jones, T.; Bamford, A.J.; Ferrol-Schulte, D.; Hieronimo, P.; McWilliam, N.; Rovero, F. Vanishing Wildlife Corridors and Options for Restoration: A Case Study from Tanzania. *Trop. Conserv. Sci.* **2012**, *5*, 463–474. [CrossRef]
66. Koen, E.L.; Bowman, J.; Sadowski, C.; Walpole, A.A. Landscape Connectivity for Wildlife: Development and Validation of Multispecies Linkage Maps. *Methods Ecol. Evol.* **2014**, *5*, 626–633. [CrossRef]
67. Lutz, A.; Atallah, A.; Holler, J. Reproduction of Makuyuni Wildlife Corridor Cost Surface Using R 2024. Available online: https://osf.io/djp97/ (accessed on 7 August 2024).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.