Bren School of Environmental Science & Management
University of California, Santa Barbara

Combining Conservation & Community Empowerment to Protect Grauer's Gorillas

A silverback Grauer's gorilla named Chimanuka that lives in Kahuzi-Biega National Park *Credit: Strong Roots Congo*

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Signature Page

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The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue.

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Acronyms

CBFM	Community-Based Forest Management
CCC	Community Conservation Committee
CF	Community Forest
DRC	Democratic Republic of the Congo
GEE	Google Earth Engine
GIS	Geographic Information System
GPS	Global Positioning System
INR	Itombwe Nature Reserve
KBNP	Kahuzi-Biega National Park
LCP	Least-cost Path
RFUK	Rainforest Foundation UK
WRI	World Resources Institute
WWF	World Wildlife Fund

Abstract

In the Sud-Kivu province of the Democratic Republic of Congo, the development of agriculture and infrastructure has fractured viable wildlife habitat between two critical biodiversity hotspots, Kahuzi-Biega National Park and Itombwe Nature Reserve. Separated by over 40 km, these protected areas contain two of the remaining populations of the critically endangered Grauer's gorilla. The communities that reside within the unprotected landscape between the parks depend on natural resources from the land for their livelihoods and subsistence. In order to establish wildlife connectivity across the landscape without infringing on local access rights, the government passed legislation permitting Community-Based Forest Management (CBFM), a strategy that intentionally involves local peoples in forest management and governance (RECOFTC, 2013; Gilmour 2016). Here, we put forth a combination of connectivity, climate projection, and socioeconomic models to identify priority conservation and restoration areas within the Kahuzi-Biega-Itombwe corridor and to understand community sentiment on forestry protections. The connectivity model highlights areas of low cost of movement within the corridor for Gauer's gorillas, which are in large part located in the eastern section of the study region as well as locations of movement constrictions (pinch points) and barriers to movement. The climate model suggests that under all future climate scenarios, optimal Grauer's gorilla habitat is likely to experience shifts in range and reduced availability of submontane and montane forests in Kahuzi-Biega National Park. The socioeconomic model highlights variation in local community opinions based on distance from the protected area and that disagreement with conservation initiatives increases with distance. These results reveal potential obstacles to the preservation of Grauer's gorillas. Community opposition to conservation efforts could dampen the observable benefits from CBFM implementation and current landscape barriers and future fragmentation due to climate change threaten connections of vital habitat. Moving forward, the Kahuzi-Biega-Itombwe Community Forest management plan should consider these results when developing spatial plans and community engagement activities to ensure the long-term coexistence of local communities and connected habitat for Grauer's gorillas.

Key words: Connectivity, Landscape Ecology, Connectivity Modeling, Climate Change Projections, Community Forestry, Conservation Planning

Significance

Global shifts in land-use activities have transformed wild, contiguous landscapes into fragmented patches to allow for human development and resource extraction (Beier & Noss, 1998; Foley et al., 2005). While landscape connectivity has proven critical to species viability, anthropogenic pressure on natural habitat is unavoidable given the current and expected rates of human population growth in developing nations (Beier & Noss, 1998; Foley et al., 2005). Community-based forest management (CBFM) was developed in the 1970s as a strategy to reverse the widespread degradation of natural lands and loss of biodiversity. CBFM refers broadly to a range of strategies in which local community practices are intertwined with government programs to promote sustainable forest management and local economy through livelihood improvements. The spectrum ranges from participatory conservation, which passively includes local peoples in government initiatives, to private ownership, where the local community is designated full control over the given forest (Gilmour, 2016).

In the Sud-Kivu province of the Democratic Republic of Congo (DRC), CBFM strategies could benefit the local chiefdoms and protect a variety of endemic species, including the critically endangered Grauer's gorilla (*Gorilla beringei graueri*) (African Wildlife Foundation [AWF], 2020). Grauer's gorilla populations have experienced population declines of 77% over the last two decades and are expected to go extinct by 2054 without concerted efforts to conserve habitat connectivity (Rainforest Trust, 2016; Plumptre et al., 2016). In Sud-Kivu, Grauer's gorilla population range extends between Kahuzi-Biega National Park and Itombwe Nature Reserve, separated by about 40 km of land occupied by seven chiefdoms (Maldonado et al., 2012).

Strong Roots Congo, a grassroots non-profit, and seven local chiefdoms are in the process of applying for community forest status to protect the area between Kahuzi-Biega and Itombwe. To date, the success of CBFM in the DRC is understudied due to the novelty of CBFM legislation in the country. To be granted community forest designation, current legislation requires local communities to implement a conservation management plan. We created models to assist with identifying planning priorities: (1) landscape connectivity, (2) community opinions and livelihoods, and (3) future climate scenarios. The connectivity model predicts Grauer's gorilla movement patterns, which help determine high-priority areas for habitat conservation and restoration. The socioeconomic model quantifies community feedback from survey questions and identifies communities that may have reservations to CBFM to prioritize for outreach. The climate model analyzes the entire landscape under multiple future climate scenarios. It identifies how Grauer's gorilla habitat is likely to change, allowing Strong Roots and the chiefdoms to proactively plan for corridor resilience. The combination of these three models will not only serve on a local scale to pinpoint high-priority management needs within the proposed Kahuzi-Biega-Itombwe corridor, but could also be used as a template to find priority areas for conservation in other emerging community forests in the eastern DRC.

Objectives

1. **Model current functional connectivity for Grauer's gorillas between Kahuzi-Biega National Park and Itombwe Nature and investigate how climate change may affect gorilla habitat.** To promote the conservation of Grauer's gorillas in the study region, it is necessary to understand gorilla presence patterns to prioritize critical areas for protection. To do this, we used a combination of expert opinion and current literature on gorilla ecology to model probable gorilla movement through the corridor and between the parks. To understand how the habitat in the corridor may be affected in the future, we used climate projections to model land cover shifts across the study region under future climate scenarios (RCP 4.5 and 8.5).

2. **Analyze local communities' opinions about existing forest protections to identify primary community concerns and the degree of support for future community forest designation.** Households in the Kahuzi-Biega-Itombwe ecological corridor will be directly engaged with forest lands and resource management. Their willing participation will depend on how involved they are in forest protection. We used the results of a local survey conducted for Strong Roots in 2020 to understand perceptions of local forestry. Local groups' views were evaluated in relation to their proximity to the boundaries of conserved land and land designated to be protected in the future. These findings were used to inform management decisions in the corridor related to sustainable development plans to gain widespread community support and increase local involvement in community forestry.

3. **Develop recommendations and a planning tool for spatial and community development planning and management of the Kahuzi-Biega-Itombwe community forest corridor.** Current and future connectivity and community perspectives were assessed to determine: (1) priority areas for current conservation, (2) key areas where reforestation activities should be prioritized, (3) highly resilient areas to prioritize for future conservation under climate change, and (4) most relevant community concerns to prioritize. We have also provided Strong Roots with a SeaSketch account populated with the results of our analyses to aid in future spatial planning and decision making. Our finalized recommendations and planning tool will help inform planning and management decisions for the community forest network to help Strong Roots achieve its goal to reduce deforestation by 13% within the study region, minimize the impact of future human land-use on gorilla connectivity, and guide restoration efforts.

Background

I. Status of Grauer's gorilla populations

The Grauer's gorilla (*Gorilla beringei graueri*), also known as the eastern lowland gorilla, is endemic to the tropical lowland forests of the Congo Basin rainforest in the eastern Democratic Republic of Congo. Grauer's gorillas play an integral role in tropical rainforest ecology by dispersing seeds and creating cleared areas of the forest where seedlings can germinate with their foraging and nesting habits (Rogers et al., 1998). Since 1995, Grauer's gorilla populations have declined by almost 77%, and now, only 3,800 individuals are estimated to remain in the wild (Plumptre et al., 2016). This rapid decline led to the listing of Grauer's gorillas as critically endangered in 2016. Historically, Grauer's gorilla range encompassed an area of about 52,000 km^2, but the species is now restricted to a total range of about 4,600 square miles, clustered into four main sub-populations within and between Kahuzi-Biega National Park, Maiko National Park, Tayna Nature Reserve, and Itombwe Nature Reserve (Maldonado et al., 2012; Junker et al., 2012).

Grauer's gorillas face multiple threats from poaching, habitat loss and fragmentation, deforestation, resource extraction activities, and civil unrest. These threats have caused a 52% decline in intact and suitable habitat over the last three decades (Junker et al., 2013). In the eastern DRC, habitat fragmentation is primarily attributed to land clearing practices for agriculture, logging, and mining. Additionally, hunting, gathering, and infrastructure development increase human access to previously inaccessible interior forest areas and thus impact the greater ecological integrity of the forest (Wilkie et al., 2000). Habitat fragmentation is a significant factor in the decline of Grauer's gorillas because it limits gene flow between the core populations and subsequently increases the risk of genetic drift and harmful mutations due to inbreeding (Baas et al., 2018; Cuni-Sanchez et al., 2019). Estimates suggest that between 500 and 2,000 individuals are needed to maintain a stable population long-term (Harcourt, 2002). Given current Grauer's gorilla population levels and increased development, scientists have estimated that without directed efforts to conserve regional habitat, the species will likely go extinct within the next 35 years (Plumptre et al., 2016).

II. Sud-Kivu case study

Kahuzi-Biega National Park and Itombwe Nature Reserve are located within the Sud-Kivu province of the Democratic Republic of Congo. These protected areas support two of the largest remaining Grauer's gorilla populations but are separated by around 3,000 km^2 of unprotected landscape (Plumptre et al., 2011) (*Figure 1*). Regional biodiversity is threatened by deforestation, poaching, and wildlife trafficking that has followed decades of civil unrest dating back to the 18th century (AWF, 2020). Kahuzi-Biega National Park was established in 1970 with the intention of conserving the biodiversity and endemic species in the area. The park covers over 6,000 km^2 and includes a mixture of dense lowland moist forest and montane forest (Yamagiwa et al., 2011). Itombwe Nature Reserve was established as a protected area in 2006 (Kujirakwinja, 2019). This reserve covers 7,000 km^2 of forest in the southern part of the province.

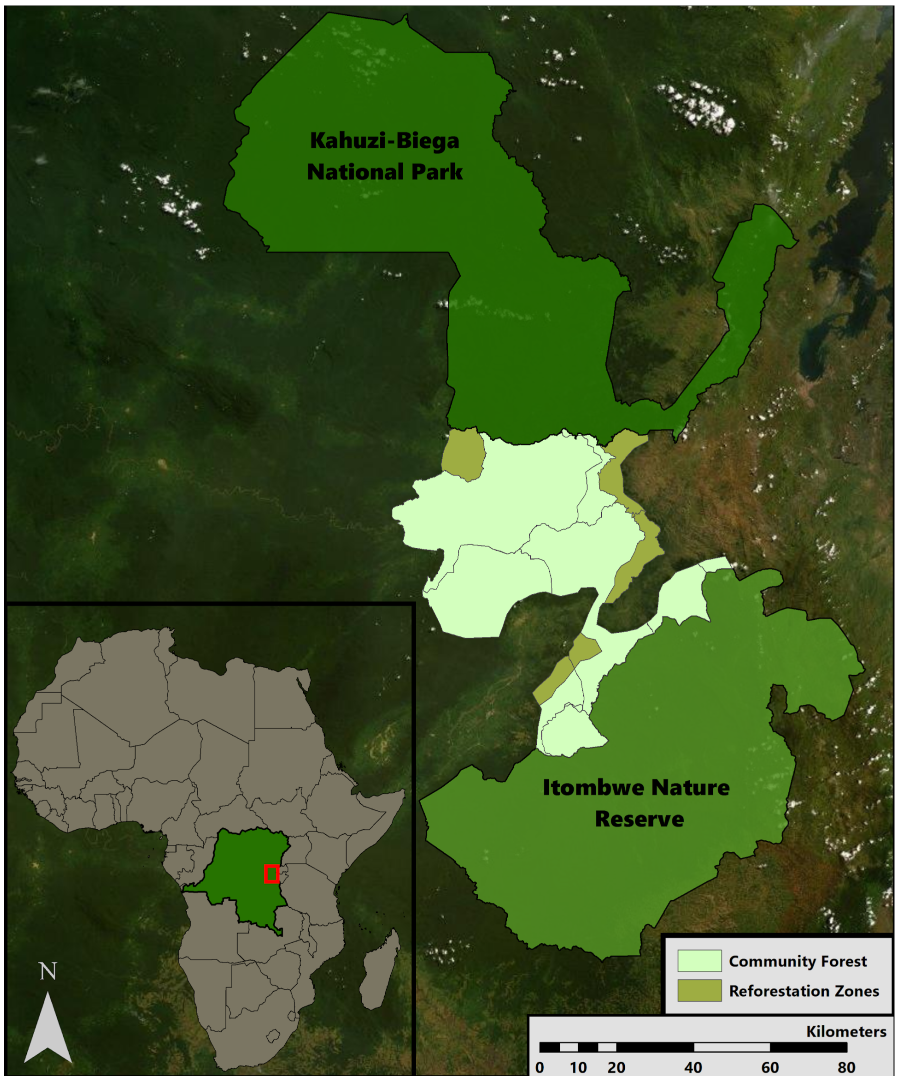

Figure 1. The case study extent in the Sud-Kivu province of the Democratic Republic of Congo. The proposed community forest habitat corridor is shown in light green, with Kahuzi-Biega National Park in the north and Itombwe Nature Reserve in the south shown in darker green. Reforestation zones implemented by the proposed community forest network are shown on the borders of the community forest in olive green.

The Sud-Kivu province has a population density of 79 people/km^2 and an annual population growth rate of 4% (Yamagiwa et al., 2011). Within the province, 58% of families live in extreme poverty and depend on forest land for building materials, food, fuel, and medicine (Strong Roots Congo, 2020). More than 90% of the rural population is dependent on subsistence farming which has become one of the largest drivers of deforestation (Moummi, 2010, Tyukavina et al., 2018). The need to access forest resources by local communities has created tensions between the park and communities and increased pressure on the lands outside of the parks (The International Institute for Sustainable Development [IISD], 2017).

In 2014, to address the challenges to conservation efforts and community stability in the nation, the DRC passed legislation to allow for CBFM. The new legislation set aside up to 75 million hectares of land that local communities could request to be put under their own authority. The government and local conservation NGOs hoped that CBFM strategies would protect intact contiguous forest and provide economic benefits to local communities (Dawson & Martin, 2015).

There are two primary objectives in most CBFM plans: to protect local biodiversity and promote the participating communities' economic and social well-being (Gilmour, 2016). These two objectives are interconnected, and the relative successes of each objective have been well documented through case studies across the globe (Gilmour, 2016; Wollenberg et al., 2007; Angelsen et al., 2009; Pretty & Ward, 2001). For example, WWF has reported positive ecological impacts—reductions in logging, poaching, and fire activity—from their community forestry projects in Indonesia and Nepal (Gilmour, 2016). However, the wide variability of CBFM application globally makes determining the success of CBFM a tedious and often unreliable process. The limitations to determine CBFM effectiveness can be attributed to three key CBFM characteristics: (1) a multifaceted approach, (2) inadequate data, and (3) novelty of implementation. The first characteristic is problematic because CBFM can be applied to various landscapes for different goals, many of which cannot be quantified or observed (Pagdee et al., 2006). Additionally, some researchers and NGOs have suggested that the lack of available data on the extent and success of CBFM makes it difficult to accurately assess forest conditions (Wollenberg et al., 2007). Finally, accurate timelines of effectiveness are skewed because when CBFM is first implemented, especially in highly degraded forests, several decades are required to achieve adequate reforestation for CF management strategies to begin (Gilmour, 2016).

In the DRC, although the government assigns legal designation of forested land to communities, donor NGOs entities play the primary role in the identification and application process that connects chiefdoms with the possibility of CBFM implementation. Local NGO Strong Roots Congo is working with seven chiefdoms to establish a community forest network that would create an ecological corridor for

Grauer's gorillas and other wildlife between Kahuzi-Biega National Park and Itombwe Nature Reserve. The network will consist of seven individual community forests, each to be managed by a separate chiefdom—Burhinyi, Luindi, Basile, Ngweshe, Itombwe, Bakisi, and the Wamuzimu chiefdom. The primary goals of the community forest network are to improve local livelihoods and protect the critically endangered Grauer's gorillas.

III. Habitat fragmentation and the importance of connectivity

Connectivity between the Grauer's gorilla sub-populations in Kahuzi-Biega and Itombwe Nature Reserve is critical for meeting the conservation goal of the Strong Roots community forest network. Habitat connectivity has been identified as a critical factor for a wide range of ecological processes including gene flow, which is particularly important for Grauer's gorillas.The low populations in both parks and the lack of genetic variation increases the species's probability of extinction (Westemeier et al., 1998). Habitat connectivity facilitates dispersal, which can significantly increase gene flow and population growth rates, thus leading to species persistence and allows species to quickly move in response to changes in environmental conditions (Allendorf et al., 2013).

Grauer's gorillas migrate widely throughout their lifetime. Grauer's gorilla home range can extend up to 42.3 km^2 over more than seven years, with seasonal shifts seen in most groups' ranges (Yamagiwa et al., 2011). Home ranges are occupied by family groups, known as troops, of around 15 to 20 members. Troops are composed of one dominant, lead male silverback gorilla, an average of three unrelated female mates, fewer than five juvenile gorillas, and numerous infants. When subordinate males reach maturity at around 15 to 20 years of age, the majority leave their natal troop in search of potential mates to draw into a new troop or a troop with an aging silverback to overthrow (Yamagiwa et al., 2011). Dispersed males depart alone or in small subordinate male groups and can travel for several years due to limited resources and/or potential mates (World Wildlife Fund [WWF], 2020). Interactions among troops are rare, and research shows that neighboring groups will limit the use of previously inhabited areas (Robbins et al., 2019). Therefore, conservation efforts intending to increase gorilla abundance require large, contiguous habitat due to dispersal needs and the tendency to avoid neighboring groups.

To promote gorilla conservation, it is important first to understand where in the landscape Grauer's gorillas are likely to travel in order to prioritize those areas for protection. We can gain understanding about places that gorillas are likely to be found through connectivity modeling (McRae et al., 2008). Habitat connectivity modeling has become commonplace in conservation plans that aim to reconnect fragmented landscapes and has proven to be a critical factor in the survival of many species. However, limitations and variability in data availability, acquisition, and methodology can reduce the quality of the connectivity analyses. While empirically-based connectivity models are considered the most robust, when empirical data is lacking for the species, expert knowledge of species behavior and habitat usage can be used to inform models (Zeller et al., 2012).

IV. Importance of climate modeling

The impacts of climate change present a fundamental threat for many species and the added uncertainty inherent in climate modeling poses serious challenges for conservation management (Keeley et al., 2018). The forest vegetation communities that make up the primary habitat for Grauer's gorillas are predicted to shift in response to climate change, with higher altitude forests predicted to decline and move upslope, and lowland forests predicted to remain stable or expand (Ayebare et al., 2013). This habitat change, as well as changes in precipitation and temperature, could result in a loss of food supply, thermal stress, and the emergence of new diseases for the Grauer's gorilla (Campos et al., 2017). Species that are unable to respond to climate shifts across the landscape are at higher risk of extinction (Thomas et al., 2004). Fragmentation reduces the ability of species to move in response to climate-driven shifts in habitat availability, making connectivity that facilitates movement into habitat that is predicted to be suitable in the future increasingly important for climate-resilient conservation planning (Keeley et al., 2018).

In other regions of the world, large protected areas connected through habitat corridors have been shown to increase population persistence and allow for range expansion despite shifts in climate (Keeley et al., 2018). However, little is known on how climate shifts will affect the distribution of species in the eastern DRC (Ayebare et al., 2013). Protecting connectivity between existing habitat and areas where habitat will persist into the future can be employed as a conservation action that promotes resilience to climate change in management plans (Hodgson et al., 2011). To ensure the long-term persistence of Grauer's gorillas it is necessary to understand how their landscape is vulnerable to climate change. Linking climate model projections with habitat models reveals how Grauer's gorilla connectivity may respond to climate change. From these connectivity projections we can preemptively identify highly susceptible corridors and key areas for conservation.

Methods

Conservation Need Assessment

We conducted a preliminary analysis of the need for conservation in the Sud-Kivu province because CBFM case studies around the globe show high variability in management tactics and success rates. To determine how successful community forestry might be for conservation in the study region, we analyzed how successful other legally designated community forests across the DRC have been in promoting conservation since their establishment. We defined conservation success as a significant reduction in local deforestation as compared to similar nearby land that has not been designated as a community forest.

To measure deforestation, we divided the DRC into five different zones: protected areas, regions of no protection, designated community forest, community forests in the process of gaining legal status, and the potential community forest region in Sud-Kivu. We also divided the DRC regionally into eastern and western provinces to compare deforestation between the two sides of the country. We evaluated the loss and gain of regional tree cover within those zones using Global Hansen Forest Loss data in Google Earth Engine (Appendix A.2-A.5). After calculating the loss and gain for each zone, the change was divided by the total area of each respective zone to find the proportion of loss for each zone. This showed us where the rate of deforestation was concentrated in the DRC, and the protection status of that land.

To determine the conservation need in the Sud-Kivu region from forest loss, we used community forests in the process of gaining legal status as the control, and compared them to designated community forests, the treatment group. This allows us to compare the treatment to a control that was on a similar trend prior to treatment, and avoids a potential comparison to areas, such as lakes and other non-forested areas, that would never be considered for CBFM. In our analysis, the control group is similar to the treatment in all ways except that the control has not yet been legally designated as a CF. We created a linear model that related deforestation rate to the establishment status of each forest. To account for average changes in forest cover over time to the entire area, we used a difference-in-difference technique to compare the average change over time in the control outcome to the average change over time to the treatment outcome. The linear model accounted for the difference-in-difference by adding a variable that related the treatment and time (Appendix A.6).

Connectivity, Pinch Points & Potential Barriers

Determining Resistance

To model connectivity, it is important to first understand how gorillas move across the landscape. If species-specific movement behaviors are well-known and documented, functional connectivity across the landscape can be easily modeled. However, animal movement is one of the most difficult behaviors to observe and quantify, and knowledge is lacking in this area for Grauer's gorillas. When species-specific behavioral data is lacking, models can be developed to assess the structural connectivity of the landscape. Structural connectivity quantifies environmental variables, such as land cover, to estimate the energetic cost of movement across the landscape (Singleton & McRae, 2013).

In order to model the environmental resistance to movement, we selected environmental variables to include based on available literature on Grauer's gorilla habitat use. The variables used to create the resistance raster were land cover, elevation, settlements, and roads. From those variables, we created a resistance raster that simulates how much resistance the gorilla encounters in each cell of the landscape. We assigned resistance values to each land cover class based on a combination of expert opinion from Strong Roots and the literature review. We assigned each class a value on a scale of 1 to 100, where 1 indicates no resistance and 100 indicates high resistance (Table 1). A value of 1,000 was assigned to classes that gorillas absolutely do not pass through, i.e., lakes and dense human settlements. We built several models in ArcGIS using Arctoolbox to re-project, re-sample, and clip the environmental data (Appendix B.1). All layers were masked to a study extent shapefile and then projected in WGS 1984 / UTM Zone 35S and resampled to a 30m cell size.

Land Cover (Appendix B.1)

We compiled data from two datasets containing land cover in the region. The first land cover map was acquired from Universite Catholique de Louvain and was created in 2012 from satellite imagery and spot vegetation reflectances (Verhegghen, 2012). The second land cover map was acquired from the 2020 Globeland30 dataset compiled by The Ministry of Natural Resources of the People's Republic of China. The ESA 2010/UCLouvain land cover map contained more detailed land cover classifications but at a 300m resolution while the Globeland30 map had less detail in classes but has higher, 30m resolution. We created a new land cover layer by reclassifying the 30m land cover dataset based on the finer classification of the 300m layer. To do this we first resampled the 300m resolution layer to 30m and clipped both layers to the same extent. To prevent interpolation, we combined these layers in ArcGIS by assigning a new value to each unique combination of values from the two input land cover layers. The combined layer had 60 unique combinations of land classification. For each unique combination we assigned the most detailed land cover classification from the input pair. The land cover type was then classified into numeric categories based on expert opinion of relative importance to Grauer's gorilla movement.

We determined current primary forest cover by using the raster for 2001 forest cover, published by GLAD, and subtracting the subsequent forest loss up until 2019, the last time data was available (Hansen et al., 2019). All land cover classified as forest outside the current primary forest area layer was then considered secondary forest for our analysis.

Settlements, Elevation and Roads (Appendix B.1)
Settlement data came from the GRID3 Democratic Republic of the Congo Settlement Extents dataset. This dataset provides settlement extent polygons grouped into three feature classes: built up areas, small settlement areas, and hamlets. DEM data was acquired from the Japan Aerospace Exploration Agency ALOS World 3D dataset. We separated the elevation data into two classes, above and below 2500m and assigned elevation above 2500m a resistance value of 70. Road data came from OpenStreetMap. We clipped the roads to the extent of our study area, buffered them to 30m, and assigned them a resistance value of 25 (Table 1).

Table 1. Resistance values for each variable considered in the assessment of Grauer's gorilla connectivity.

Variable	Classes	Resistance Value
Land Cover	Primary Forest	5
	Secondary Forest	1
	Forest Savanna Mosaic	40
	Savanna Woodland/Tree Savanna	50
	Cultivated Areas	65
	Shrubland	85
	Wetlands	30
	Grassland	95
	Artificial Surfaces	1000
	Water Bodies	1000
Elevation	> 2500 m.a.s.l	70
Anthropogenic Features	Built Up Areas	1000
	Settlements	1000
	Hamlets	100
	Roads	25

Connectivity
Connectivity is a measure of how much the landscape aids or obstructs the movement of wildlife between core areas. The connectivity of the landscape can be represented as the inverse of the resistance value of each cell, modeled as a current that passes through each cell between the core areas (Singleton & McRae, 2013). We used the resistance raster and the Linkage Mapper 2.0.0 toolbox in ArcGIS 10.8 Model Builder to develop a model of connectivity for Grauer's gorillas (Appendix B.2) (Anantharaman et al., 2020). Linkage Mapper uses electrical current theory, which is based on electrical currents and resistance, to predict how wildlife will move through a landscape (McRae et al., 2008). To model connectivity between core habitat patches, Linkage Mapper determines the density of current flow at each cell. High current densities occur where

resistance is lower, which corresponds with low cost of movement. This means that the target species is more likely to move through those cells. Using the total accumulated movement resistance, Linkage Mapper calculates the cost weighted distances of all cells to a core. Adding the cost weighted distance values between two locations produces a composite raster of the relative connectivity value of each cell and displays the movement costs of all pathways between the cores (Shah & McRae, 2008). Circuitscape assumes that habitat suitability is the same as habitat permeability, thus areas that are identified as low cost of movement are also suitable for the species to persist.

We initially assigned Kahuzi-Biega National Park and Itombwe Nature Reserve as the habitat cores and simulated the flow of current from one core to the other across the resistance raster. Since Kahuzi-Biega and Itombwe are irregularly shaped parks, the width of the corridor between them is variable. This creates bias in the results by skewing the least-cost path toward the eastern part of the study area where the Euclidean distance is shortest between the core areas. In order to eliminate the bias from the variable Euclidean distances between the park boundaries, we created parallel polylines near the borders of Kahuzi-Biega and Itombwe to represent the core areas. This created a conductive landscape with a constant width, so we could evaluate the connectivity of the corridor network based on the landscape resistance rather than the distance between core area boundaries.

LCP & Least-Cost Corridor

We used the Build Network and Map Linkages tool to identify the least-cost path (LCP) and the surrounding least-cost corridor. The LCP indicates the 1-cell width pathway with the lowest cost-weighted-distance between the core habitats (McRae et al., 2012). The LCP is measured in two distances: Euclidean and cost-weighted. Euclidean distance is the actual distance in kilometers of the LCP. The cost-weighted distance is the weighted Euclidean distance and resistance, which accounts for physical distance and energetic cost of traversing the landscape for Grauer's gorillas. The least-cost corridor is the set of cells for which the least-cost path distance between two sources passing through the cell falls below a user-defined threshold (Singleton & McRae, 2013). We set the corridor size threshold to 100 kilometers to create a corridor with a width of 100 km across. We determined that a 100 km threshold was appropriate as it was wide enough to display the entire width of the corridor but narrow enough to offer a high resolution display of connectivity within the corridor.

Pinch Points

We used the Pinch Point Mapper tool to identify pinch points, constricted areas where current concentrates in the landscape, which represent areas through which Grauer's gorillas have a high likelihood or necessity of passing through. The model assumes that species have no memory, i.e.random walk, and always move through the closest cell with the lowest resistance, thus the current will concentrate in areas where the corridor narrows (McRae et al., 2008). Places with high current flow indicate that altering or removing those linkages would have a significant negative impact on overall connectivity. Pinch points indicate key areas for conservation that, if lost, might sever connectivity between Kahuzi-Biega and Itombwe. We analyzed the pinch points within 25 kilometers of the least-cost path by setting the cost weighted corridor width cutoff to 50 kilometers. Focusing on pinch points within a 25 kilometer radius of the least energetically costly path through the corridor allowed us to find high priority areas for gorilla movement across the entire width of the corridor network.

Barriers

To determine which areas within the corridor impede connectivity we used the Barrier Mapper tool to identify barriers - landscape features which obstruct movement between ecologically important areas - where restoration could most improve connectivity (McRae et al., 2012). Barriers reduce the connectivity value of the corridor as a whole, as they impede the most efficient route to traverse. Impermeable barriers, such as permanent human settlements and bodies of water, completely cut off movement and can not be restored. Partial barriers, such as land cover types that are less suitable but traverable, can be reduced by restoration, as ecological restoration decreases the resistance value of the cell and results in a higher current through the cell (McRae et al., 2012). Barriers created by fragmented landscapes from past agricultural activities or other human land uses can be restored by planting trees and native vegetation.

If the resistance within the corridor is reduced, then the cost-weighted distance of the best pathway between the core areas will also be reduced. Barrier Mapper identifies where reducing resistance would lead to the greatest reduction in cost-weighted distance, by quantifying the change in effective cost-of-movement across the corridor when the resistance of a specified area is reduced. If the least-cost-distance after restoration is less than the current least-cost-distance, then the cost-weighted distance of the LCP is reduced, and connectivity would increase between the protected areas. The proportional improvement of the least-cost-distance relative to the unrestored least-cost-distance describes the relative impact of the barrier on quality and location of the LCP. We set the parameters of the tool to a minimum and maximum barrier detection radius of 40 meters and 400 meters, respectively, allowing the model to detect barriers between 0.5 and 50 hectares in area. We chose areas between 0.5 and 50 hectares for barrier detection to provide realistically sized areas for potential restoration in the Strong Roots corridor.

Community Wellbeing & Opinions

2020 Socioeconomic Study

Strong Root aims to conserve Grauer's gorillas and other wildlife by engaging local communities and indigenous people in conservation and improving their well-being. The Gender and Development Research and Expertise Center of Bukavu designed and performed a survey on Strong Roots' behalf that explores the social makeup of a sample group that lives in the Kahuzi-Biega-Itombwe ecological corridor.

Respondents provided information on aspects of their lives in a social, economic, political, and cultural context. This information informs the development of forest governance and management in the territory of Mwenga in Sud-Kivu, which encompasses the Wamuzimu, Basile, Luindi, and Burhinyi chiefdoms and twenty-seven local groupings.

The survey consisted of seven sections:

1. Sociodemographic characteristics of households - General information on households, education, and training, as well as professional involvement in the study environment. Information was self-reported.
2. Living conditions of households - Focuses on the standard of living of households in the corridor. Economic activities and an estimate of income/expenditure are summarized with an estimation of financial literacy. Information was self-reported.
3. General knowledge of protected areas - Fourteen items over two dimensions: accessibility or availability to basic infrastructure and responsibilities of the actors. Responses to the items were collected on a four-point Likert scale ranging from 1 (total agreement) to 4 (total disagreement).
4. Governance of community forestry - Fifty-five items spread over eight dimensions: the establishment of the limits of the Itombwe Nature Reserve, the relationship with law enforcement, the relationship with the Community Conservation Committee (CCC), participatory community management of nature reserves, environmental management, various conflicts, relations with the State and NGOs, as well as access to resources. Responses to the items were collected on a four-point Likert scale ranging from 1 (total agreement) to 4 (total disagreement).
5. Natural resource use for local communities - Thirty items over one dimension to retrieve information on how local communities use natural resources. Responses to the items were collected on a four-point Likert scale ranging from 1 (total agreement) to 4 (total disagreement).
6. Environment and climate - Items on the environment and the climate like observations, concerns, and dependence. Yes/no responses were collected.
7. Gender and indigenous rights - Items concerning activities and rights of women, as well as indigenous people. Yes/no responses were collected.

Proximity Analysis

Based on the geographic coordinates of respondents' households collected after survey completion, we calculated the distance to the boundary of Itombwe Nature Reserve—the nearest protected area to the territory of Mwenga, which is the survey's study site.

Due to the imperfect nature of field collection, gaps were present in collected household locations throughout the dataset, with 7% of the respondent household locations missing. Based on the timestamp indices of survey completion, we linearly interpolated the given latitude and longitude coordinates to find the intermediate points.

Linear interpolation provides us with a household location that could be plausible for the missing respondents. For survey responses that could not be confidently interpolated, we set minimum and maximum constraints and randomized a location. We set the constraints according to the respondents' respective chiefdom and community grouping to generate a random point in the area.

Using the household coordinates for all the respondents, we then calculated the distance in meters of each household from the Itombwe Nature Reserve's boundary. To account for the uncertainty associated with the missing coordinates, we created five different datasets by randomizing points of missing households five separate times. Each dataset had slightly different values and were analyzed using the Near tool in ArcGIS 10.8 (Appendix C.1) The results from the five full iterations were averaged giving us a final spatial distance, in meters, from Itombwe. This provided us with a final estimate of a respondent's distance to the Itombwe Nature Reserve.

Pinch Point Sentiment Analysis

The pinch points determined from our connectivity analysis highlight the critical habitat connections where the flow of species movement becomes restricted (McRae et al., 2008). The three pinch points identified in our connectivity and barriers analysis are located between settlements and include critical conservation areas that will be integral to our client's success in the future. If these locations are lost, connectivity will be completely severed for Grauer's gorillas between Kahuzi-Biega National Park and Itombwe Nature Reserve, so conservation and development planning must be prioritized here. In order to examine public sentiment within and near the pinch points, we calculated the distances from respondent households to the nearest pinch point identified in the southwestern reforestation zone in the Mwenga territory. To make final recommendations for sustainable development near the pinch points, we considered responses from households within 10,000 meters of a respective pinch point (Appendix C.2).

Strong Roots Congo is working on development at the community level, so we used the average distance by local grouping to each protected area's boundary. We calculated descriptive statistics for sections four, five, and six of the survey, which assesses the local perceptions of protected areas, community forestry governance, and local natural resource use, respectively. To determine the strength of a linear relationship we used a Spearman's correlation coefficient, which measures the plausibility and strength of a monotonic relationship (Gatiso, 2019). For the purposes of our analysis, we sought to determine if a relationship exists between distance and distinct survey items. Likert scale questions allowed individuals to express their relative level of agreement or disagreement with information presented on a variety of topics. These responses ranged from 1 (total agreement) to 4 (total disagreement). We assessed whether the responses moved in a specific direction based on increasing distance from the protected area in question–Itombwe Nature Reserve. A response will be considered correlated to distance if the Spearman's correlation coefficient (rho) is between 0.5 and 1–an indicator of a moderate to strong relationship (Gatiso, 2019).

The statements with a relationship to distance are representative of areas in which to improve public opinion and subsequent community engagement. The aim of this exploration is to highlight the barriers that local communities may face that hinder meaningful participation in community forestry efforts.

Future Climate Scenarios

Our climate analysis uses the species distribution software, MaxEnt, to model the probabilistic distribution of the suitable habitat types for Grauer's gorilla within our study area. Species distribution models (SDMs) estimate the statistical relationship between known species occurrences and the environmental and spatial characteristics of those locations to create maps which depict the probability of species occurrence (Franklin, 2010). All species have specific habitat requirements, or a fundamental niche, which can be described by the habitat's environmental factors, such as temperature and vegetation type. Habitat suitability is determined by these environmental factors and describes how well the habitat meets conditions that allow for long-term survival of the target species. Thus, deterministic environmental factors can be used to approximate where in the landscape habitat exists that satisfies the necessary conditions for that species' fundamental niche (Store & Kangas, 2001). These models are widely used to inform conservation strategies for wildlife management because they help in understanding both the niche requirements of a species as well its potential distribution (Guisan & Thuiller, 2005; Hirzel et al., 2006). It is important to note that the fundamental niche describes the total potential area of suitable habitat for the species and may differ from the species realized niche, which is the amount of the fundamental niche utilized by the species. Traditionally SDMs have used presence/absence data, however true absence data is often unavailable or difficult to verify, especially for rare or endangered species.

Maxent is a maximum entropy software for modeling species distributions from presence-only data by using machine learning to estimate the relationship between species presence points and the environmental characteristics related to habitat suitability (Elith et al., 2011). The species-environmental relationship describes the occupied niche of the species which is projected to identify the fundamental niche for the species. Maxent estimates the probability distribution of the species' fundamental niche by finding the most uniform distribution of sampling points compared to background locations when subject to a set of constraints derived from data which represents the information about the target distribution (Baldwin, 2009). Each presence point represents a sampling location and the environmental variables at that point represent the information available about the suitable habitat conditions (Phillips et al., 2006). Maxent then evaluates the relationship between the environmental conditions and species presence against the background conditions and returns the most randomly distributed model of probability that exists within the environment constraints of the study area. The output is a raster that illustrates the predicted probability of habitat suitability from 0, low, to 1, high, for the entire landscape.

Once the species-environmental relationship has been quantified, Maxent can be used to predict future distributions under climate change. The species-environmental relationship is determined by the present day environmental conditions and then the model is projected by applying it to environmental conditions under different climate scenarios. The result is a prediction of the future distribution of the species' fundamental niche. SDM niche prediction models only consider the environmental variables that control distribution and do not consider species evolution, dispersal processes, or the temporal scale needed for species to respond to climate change. Thus, correlation between presence and environmental conditions does not necessarily guarantee that a species will successfully occupy the predicted distribution. However, species distribution modeling is useful for understanding potential regional shifts in species distribution and the risk of habitat loss (Liu et al., 2016).

For our analysis we modeled the probabilistic distribution of vegetation communities that represent the main habitat for the Grauer's gorilla and predicted how these will respond under future climate scenarios (Ayebare et al., 2013). This approach can be used to identify potential shifts in the dominant vegetation communities and help determine which communities are vulnerable to climate change. Predicting suitable areas for entire vegetation communities is a novel use of species distribution modeling, but it uses the same logic as single species models based on the assumption that species within dominant vegetation communities have similar niche requirements (Ponce-Reyes et al., 2012).

We considered three of the five main vegetation types utilized by Grauer's gorilla: montane forest, submontane forest, and dense moist forest in our future climate analysis. We did not include savannah in the analysis because savannah emerges when other vegetation types are altered by human activity or disturbance. Without accounting for the role of anthropogenic and natural disturbance in determining the distribution of savannah, using niche-based models to predict distributions changes for savannah would lead to inaccurate predictions. Detailed modeling of future anthropogenic land use predictions and disturbance was outside of the scope of this study. We omitted bamboo forest from our analysis as well due to a lack of data on the extent of bamboo forest from which to sample occurrence points from.

Maxent Species Distribution Model

Variable Processing

Based on the Globeland30 and the UCLouvain land cover data, we applied the same methods used to create the resistance raster land cover layer to create separate layers for the distribution of montane forest, submontane forest, and dense tropical forest. This time we combined the 300m resolution vegetation map with the 30m resolution forest extent keeping the forest classifications from the 300m resolution map. We classified all unclassified forest cells into the three forest types based on elevation. Unclassified cells above 1500m in elevation were classified as montane, cells 1000m-1500m were classified as submontane, and cells below 1000m were classified as dense tropical forest. While forest type is dependent upon climate variables, elevation can be used as a proxy for those climate variables because climate variables are strongly associated with elevation in this region.

We selected environmental variables for their ecological importance to the distribution of the three forest types (Ayebare et al., 2013). The environmental variables we selected for Maxent were lithography, soils, and bioclimatic variables (Table 2). The lithography data was acquired from the U.S. Geological Survey / The Nature Conservancy African Surficial Lithology dataset and soils data was obtained from the FOA - UNESCO Digital soil map of the world. For each climate model, we used the 19 standard bioclimatic variables from the Chelsa dataset which are derived from the monthly temperature and rainfall values.

Table 2. Predictor variables used for modeling the distribution of montane forest, submontane forest and dense moist tropical forest.

Variable	Description
bio1	Annual Mean Temperature
bio2	Mean Diurnal Range
bio3	Isothermality
bio4	Temperature Seasonality
bio5	Max Temperature of Warmest Month
bio6	Min Temperature of Coldest Month
bio7	Temperature Annual Range
bio8	Mean Temperature of Wettest Quarter
bio9	Mean Temperature of Driest Quarter
bio10	Mean Temperature of Warmest Quarter
bio11	Mean Temperature of Coldest Quarter
bio12	Annual Precipitation
bio13	Annual Precipitation
bio14	Precipitation of Driest Month
bio15	Precipitation Seasonality
bio16	Precipitation of Wettest Quarter
bio17	Precipitation of Driest Quarter
bio18	Precipitation of Warmest Quarter
bio19	Precipitation of Coldest Quarter
soil	Map of the soils
lithography	Map of the geologic parent material

Our future projections are based on 5 climate models, CESMI-BGC, MPI-ESM-MR, ACCESS01, MICROC5, and CMCC-CM, to represent the inherent uncertainty in climate model projections. Models were chosen based on a review of commonly used models for our study region and selected for lowest interdependence. We projected the models to 2050 and 2080 for two climate change scenarios, RCP 4.5, an intermediate emission scenario, and RCP 8.5, a worst-case scenario.

Species Distribution Modeling

Maxent requires the input of a point dataset of species presence to use as sampling locations for the predictor variables. To create presence points from the land cover layers we created datasets of 1,000 randomly sampled presence points per forest type, separated by a minimum of $1km^2$, from within the current extent of each forest type (Ayebare et al., 2013). We used the default Maxent parameters for modeling the distribution of all three vegetation types (convergence threshold of 0.00001, maximum number of background points =10,000, regularization multiplier=1) but selected linear, quadratic, and product for the feature classes, as we found these produced smoother response curves than Maxent default indicating less complexity in the model. Each model run was validated using a 30-fold cross validation, where the presence points are randomly split into equal sized groups or folds, in this case 30, and the model is created leaving out each fold in turn. The excluded folds are used as test data to evaluate the model.

We used the average area under the receiver operating curve (AUC) across the 30 replicates as the metric to evaluate model performance. For Maxent models, AUC indicates how well the model is capable of identifying a true presence from an absence. The higher the AUC the better the model is at distinguishing between a presence site and an absence site with 1 indicating perfect model fit (Fielding & Bell, 1997). When using AUC to evaluate a species distribution model an AUC value >0.9 is considered an excellent model fit, 0.8.–0.9 is very good, 0.7-0.8 is good and <0.7 is considered uninformative (Baldwin, 2009; Swets, 1988). It is important to note that AUC values tend to be higher for species with narrow ranges relative to the study area and is an artifact of the AUC statistic and does not necessarily mean that the models are better (Phillips, 2017). To account for this, we expanded the study extent to the area of the Sud-Kivu, Nord-Kivu, and Maniema provinces for the Maxent models.

Using these parameters, we predicted the current probability of habitat suitability for montane, submontane, and dense moist tropical forest and used these outputs to project the distribution of each forest type to the year 2050 and 2080 for each GCM and RCP combination. For the future distribution predictions, we used the same static predictor variables (lithology and soil) from the current distribution models and the predicted versions of the 19 bioclimatic variables for each climate scenario.

The Maxent outputs resulted in 20 potential future habitat suitability distribution maps for each forest type. Each output shows the average probabilistic distribution of suitable habitat conditions under that climate change scenario on a continuous scale.

Climate Risk Analysis

Calculating the change in the extent of each forest type requires binary models of distribution and a threshold value is needed to transform the continuous habitat suitability results into a binary presence/absence result (Liu et al., 2016). We used the "equal training sensitivity and specificity logistic threshold" value for each model to convert the Maxent outputs into binary layers (Ayebare et al., 2013). This threshold value is where positive and negative observations have an equal chance of being correctly predicted by the model (Freeman & Moisen, 2008). The suitability distribution was divided into two classes, with all values above the threshold value assigned as 1, indicating species presence, and values below the threshold assigned 0 for absence.

We used a maximum consensus approach to combine the predicted results of the five GCM models for each climate scenario to account for the uncertainty in climate models. Only cells that were predicted as present by all five models were kept in the final binary prediction layers for each forest type. We chose to select only points present in all five models, as this represents the most conservative estimate of future forest extents for each climate scenario. This choice accounts for the uncertainty in climate modeling and minimizes the risk that resources will be spent conserving future unsuitable habitat. We then compared the extent and calculated the difference in the area of each forest type from the current distribution to 2050 and 2070 under the RCP 4.5 and the RCP 8.5 emission scenarios. This will provide us with the percent change in amount of Grauer's gorilla habitat in our study area and show us where habitat shifts will occur spatially in relation to the corridor.

Resilience Analysis

The aim of this analysis is to identify habitat areas that will be resilient to climate change, indicated by overlap between the future and current habitat distributions. These areas would be considered "no regrets" areas for conservation prioritization because they would likely provide benefits for Grauer's gorillas today and in the future (Heller & Zavaleta, 2009). To identify areas of resilience we added the current and future binary predicted distributions created using the maximum conscience approach from the previous analysis. The binary future presence prediction values were reclassified from 1-0 to 2-0 so that the sum of the binary inputs produce a map with 4 values for each climate scenario: 0- no predicted presence for that vegetation type, 1 - presence predicted currently but not in the future, 2 - presence predicted in the future but not currently, and 3 - presence predicted both currently and in the future (Ayebare et al., 2013; Vos et al., 2008). Areas of overlap (value = 3) include two possible scenarios; they can be areas where the entire future distribution of the forest type is confined to a smaller area within the current distribution, or they are areas that will act as bridges linking partially overlapping current and future distributions. Finally, we aggregated the results for the three forest types to create maps of combined Grauer's gorilla habitat resilience areas under each climate change scenario.

Results

Conservation Need Assessment
Deforestation analysis across the five zones of interest revealed that forest loss has steadily increased across the entire DRC since the year 2000. Regional analysis based on the geographic location—east versus west—of community forests revealed that deforestation has been proportionally greater in the eastern provinces than in western provinces over the last two decades. Percent tree cover loss in the Sud-Kivu province was 9.8% which is 2.75% higher than the national average. Deforestation was even higher in the study region, with a calculated 10.2% loss of tree cover in the last two decades.

The linear model for the difference-in-difference model indicates that there is an increase in proportional loss by 0.00067 when an area has legal community forest designation, but with an insignificant probability: 95% CI [-0.0025, 0.0039]. Therefore, there is no significant impact of the treatment, legal designation, on deforestation on timescales of less than three years (*Appendix A*).

Connectivity, Pinch Points & Potential Barriers
LCP & Least-Cost Corridor
The least-cost corridor (*Figure 2*) displays the cost of movement across the landscape, from the lowest cost of movement in dark green to the highest cost in white. Connectivity is highest on the eastern side of the proposed corridor network, with the lowest cost of movement occurring in the secondary submontane forests in the east. The highest cost of movement occurs across the central-western section of the corridor. The holes in the corridor represent the established settlements that have too high of a resistance for gorillas to travel through. The least-cost path (LCP), shown in blue, is approximately 76.86 km in Euclidean distance between the protected areas, with a cost-weighted-distance of 158.25 km. The LCP passes through 2 of 7 community forests and 3 of 5 reforestation zones. There are several high connectivity pathways adjacent to the LCP, that are displayed in dark green, which implies that there is redundancy in the connectivity pathways within the corridor network. This indicates that Grauer's gorillas will likely traverse this area in addition to the LCP.

Pinch Points
Several pinch points of movement are located in the area between the respective northern and southern portions of the proposed Kahuzi-Biega-Itombwe corridor. This area is more densely populated, and land-use change is more prevalent. Thus, the pinch points identify key locations of Grauer's gorilla connectivity through the anthropogenically dominated portion of the landscape. The LCP goes through pinch point *A* and pinch points *B* & *C* (*Figure 2*) were identified as areas of high connectivity value. Pinch point *A* is the only pinch point that is within the currently proposed corridor boundaries. The location of the pinch points in areas of high

connectivity value indicates the importance of these areas to Grauer's gorilla connectivity. The loss of suitable habitat in these areas due to land use change or climate change could sever the connectivity between the two protected areas completely.

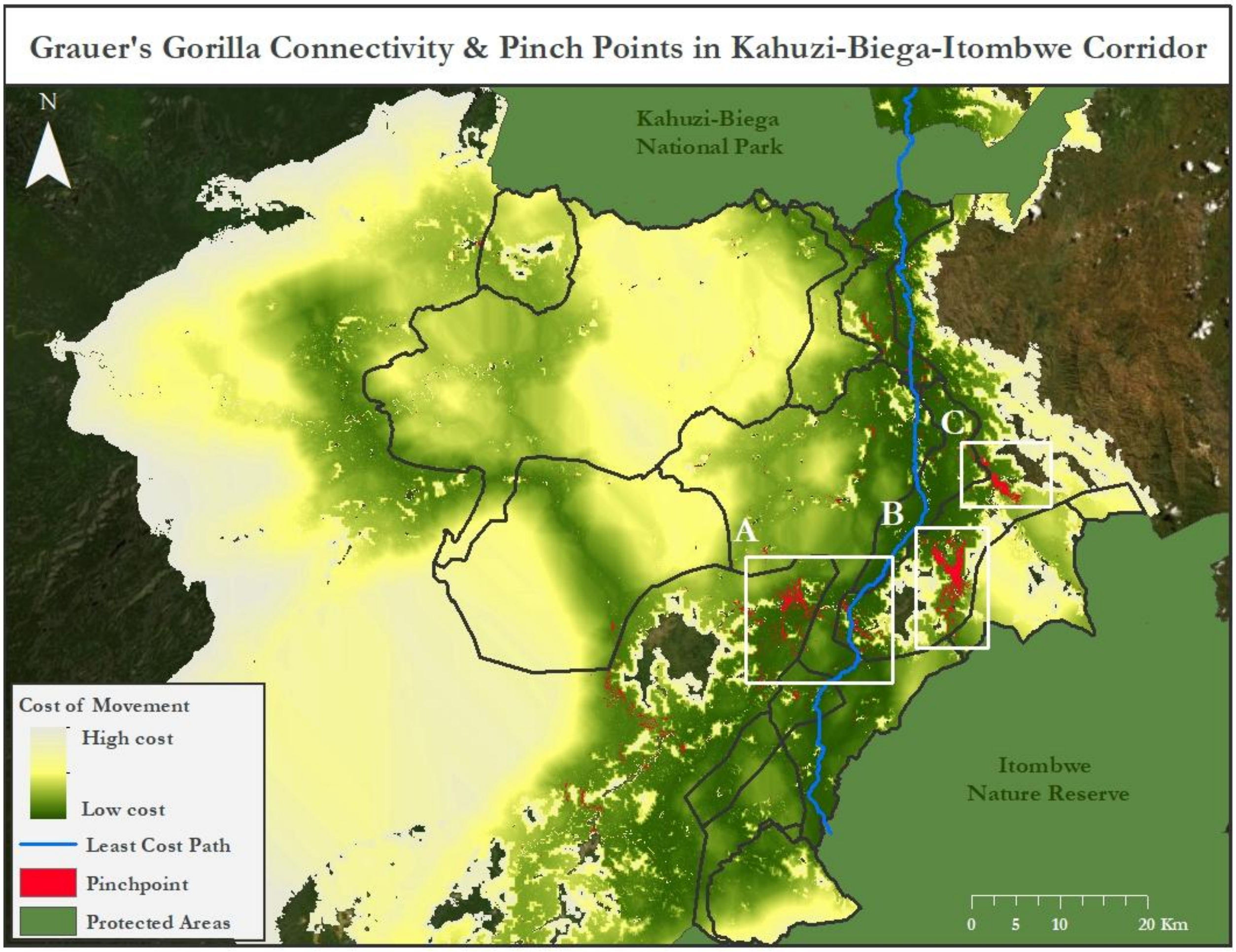

Figure 2. Grauer's Gorilla Connectivity & Pinch Points in the Kahuzi-Biega-Itombwe corridor. Critical habitat connections (*A*, *B*, *C*) where flow becomes constricted, called pinch points, are highlighted in red between the two protected areas. Dark green areas represent areas of lower movement cost and higher connectivity. White areas represent areas of higher movement cost and lower connectivity. The least-cost path, shown in blue, represents the lowest cost-weighted-distance route between Kahuzi-Biega and Itombwe.

Barrier Mapper

The barrier analysis identifies barriers, which are areas along and adjacent to the least-cost path (LCP) of higher resistance, where ecological restoration could most improve connectivity. Barriers that have the highest impact on the cost-weighted distance of the LCP are shown in yellow, with the size of the bubbles representing the size of the barrier, between 0.5 and 50 hectares in area (*Figure 3*). The largest barrier is located in the southwestern portion of *A* (*Figure 3*). Prioritizing restoration of this barrier would most significantly reduce the cost-weighted distance of the LCP and enhance overall connectivity. Due to the severity of this barrier, the analysis produced a second potential route for the LCP, shown by the smaller barriers in the eastern section of *A* (*Figure 3*). Restoration of the barriers along the LCP would improve the connectivity value of the existing LCP without changing its location. If the restoration of the smaller barriers to the east reduced resistance enough to create a less energetically-costly route, the LCP would instead be re-routed to the east.

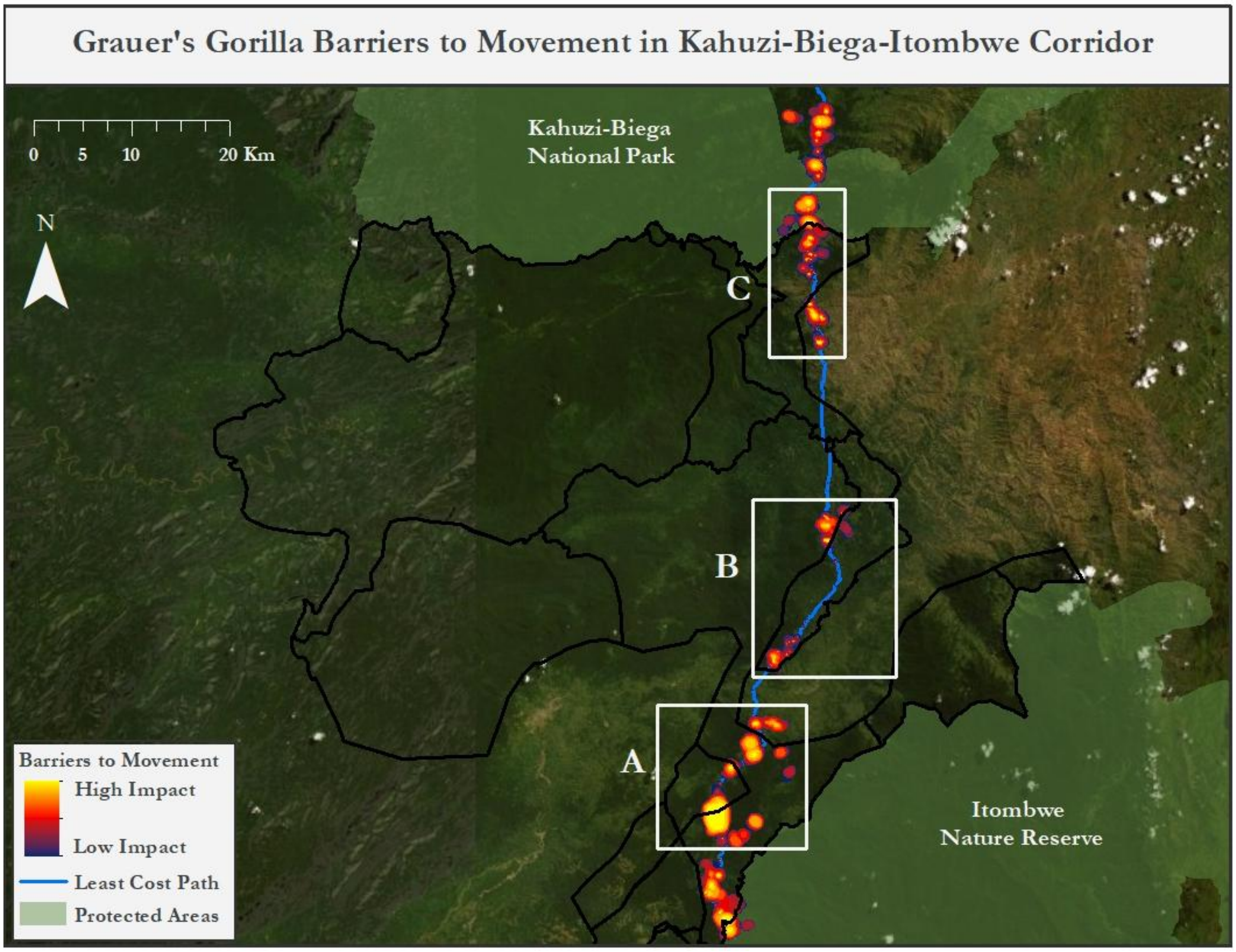

Figure 3. Grauer's Gorilla Barriers in the Kahuzi-Biega-Itombwe corridor. Barriers to gorilla movement between .5 and 50 hectares along and adjacent to the least-cost path were identified as yellow circles, with size representing the area of the barrier. Restoring barriers along the LCP would strengthen the existing corridor (reduce effective resistance) without changing its direction, while restoring barriers that do not follow the LCP (shown to the east in *A*) would alter its route. The areas *A*, *B*, and *C* highlight three proposed reforestation zones that have barriers of high restoration potential.

Many of the identified barriers are located within three of Strong Roots proposed reforestation zones (*A*, *B*, and *C* in *Figure 3*), where restoration is likely to occur in the near future. Further analysis of the underlying features of the barriers reveals that they are partial barriers; areas of slightly fragmented forest with no competing land use, such as active agriculture or development. Ecological restoration through reforestation is likely to be successful in these areas and would improve the current connectivity of the landscape. Reforestation of any of the identified barriers would reduce the cost-weighted distance of the LCP and least-cost corridor, which would enhance overall connectivity across the corridor network.

Community Opinions on Forest Protection

Proximity Exploration

Based on the initial analysis of public perception using a community's distance to Itombwe Nature Reserve, nine items across the three sections were correlated with distance (*Table 3*) based on a Spearman's rho value from 0.5 to 1, which indicates a moderate to strong linear relationship. Survey respondents who live near Itombwe tend to agree with the statements about accessibility, governance, and resource use. Survey respondents that are farther from the park tended to disagree with the presented statements.

Table 3. Significant values of Spearman's Rank-Order Correlation Coefficient on survey responses corresponding to distance to the protected area Itombwe Nature Reserve (INR).

Survey Statement	Spearman's ρ
Our areas are linked by roads in good condition.	0.81
The agricultural service roads are developed by the chiefdom.	0.67
Our chiefdom is full of road infrastructure in good condition.	0.74
Road infrastructure in poor condition is being developed by the competent services including the route office, Roads and Drainage Office (OVD), etc.	0.69
Vehicles can easily access community forestry.	0.77
The CCCs play the role of interface between the population and officials of the INR.	0.80
The population cannot take an interest in INR and its environment since the population is excluded from any decision-making power concerning the INR.	0.75
The INR is under pressure from the local population because it contains land whose development is essential to the populations.	0.69
The main cause of deforestation is the development of illegal logging.	0.51

Five items regarding general knowledge of protected areas and overall accessibility were associated with the protected area's distance from each community surveyed (*Figure 4*). These sentiments are associated with road condition and infrastructure that dictates whether there is easy access to the protected area. Across all presented survey items, the presented statement: "our areas are linked by roads in good condition" had the most significant linear relationship with distance. To understand this perception distribution, the underlying patterns of road construction projects and maintenance, and the underlying motivation for that work could be investigated in the region.

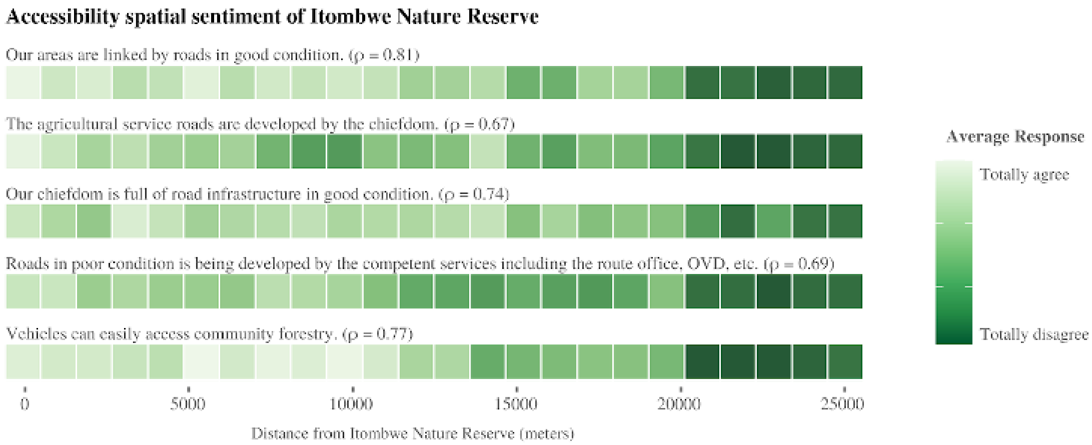

Figure 4. Heat map of public perception of Itombwe Nature Reserve's accessibility in Sud-Kivu, DRC. Using Likert-scale survey responses, (from 1-total agreement, to 4-total disagreement) public opinion on the accessibility of protected areas, specifically Itombwe Nature Reserve. The x-axis visualizes the average distance from the park. The y-axis represents statistically significant survey topics. Darker coloration of squares indicates a higher average of disagreement on the topic. Lighter coloration indicates relative agreement with the topic at hand. The rho value is a strength indicator of a monotonic relationship between the statement and distance to INR using Spearman's Rank-Order Correlation.

Two items from the local community forestry governance topics were correlated with the protected area's distance from each community surveyed (*Figure 5*). These sentiments were associated with the Community Conservation Committee's (CCC) role and the population's inclusion in the environmental and protected area decisions. Communities closer to the nature reserve experience greater satisfaction with governing groups, particularly the CCC. This suggests that outreach programs based out of Itombwe have been succeeding at building local community improvement near the park but highlights an opportunity to strengthen the relationship between local populations further from the nature reserve and authoritative groups. This also indicates that community improvement outreach could be beneficial for generating satisfaction in communities near the community forests.

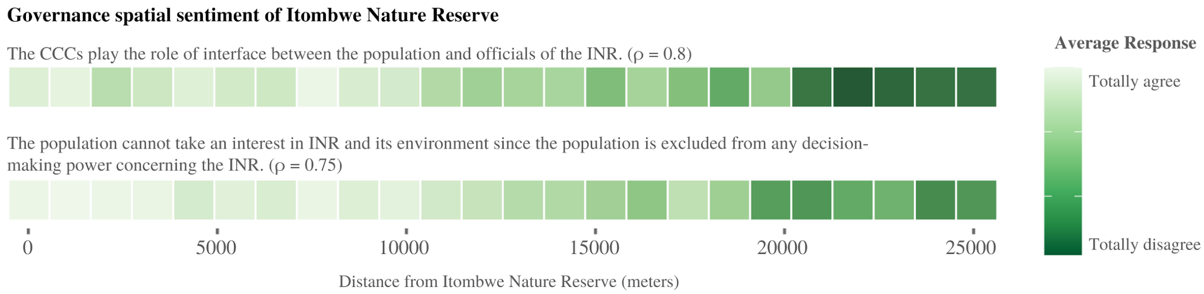

Figure 5. Heat map of public perception of Itombwe Nature Reserve's governance in Sud-Kivu, DRC. Using Likert-scale survey responses, (from 1-total agreement, to 4-total disagreement) public opinion on the governance of protected areas, specifically Itombwe Nature Reserve. The x-axis visualizes the average distance from the park. The y-axis represents statistically significant survey topics. Darker coloration of squares indicates a higher average of disagreement on the topic. Lighter coloration indicates relative agreement with the topic at hand. The rho value is a strength indicator of a monotonic relationship between the statement and distance to INR using Spearman's Rank-Order Correlation.

On topics of natural resource use for local communities, two items are associated with the protected area's distance from each community surveyed (*Figure 6*). These sentiments are associated with the population's role in land development and unlawful logging. A central goal of CBFM is to expand local communities' capacity to manage natural resources themselves. Those that are further from the protected area could potentially benefit from education and action outreach that focuses on educating and empowering groups that strongly depend on local resource use.

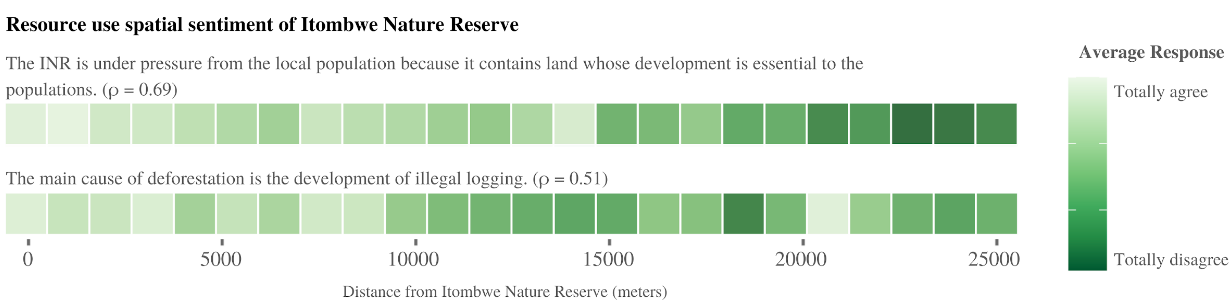

Figure 6. Heat map of public perception of Itombwe Nature Reserve's community resource use in Sud-Kivu, DRC. Using Likert-scale survey responses, (from 1-total agreement, to 4-total disagreement) public opinion on the public's use of natural resources in protected areas, specifically Itombwe Nature Reserve. The x-axis visualizes the average distance from the park. The y-axis represents statistically significant survey topics. Darker coloration of squares indicates a higher average of disagreement on the topic. Lighter coloration indicates relative agreement with the topic at hand. The rho value is a strength indicator of a monotonic relationship between the statement and distance to INR using Spearman's Rank-Order Correlation.

Pinch Point Population Response

After identifying the three pinch points within the community forest network near Itombwe Nature Reserve, we used the survey information to advise recommendations on the communities that are within 10,000 meters of each pinch point. If conservation activities are pursued in these areas, chiefdoms and local NGOs could prioritize sustainable development in the respective area to gain public approval. Responses are interpreted on the same Likert scale used in the previous survey analysis (one indicating total agreement and four indicating total disagreement).

One hundred and fifty-eight households are within 10,000 meters of pinch point *A*. The distribution of responses indicates a relatively higher level of public disagreement with the statements presented on access to protected areas. The average response to items in this section was 3.11 (disagree). Additionally, the average response on items related to governance was 2.46 agree), and the average response on local resource use was 2.33 (*Figure 7)*. This indicates that the households in proximity to pinch point *A* don't feel that they have access to protected areas but do somewhat agree that governance of protected areas is effective and that there is pressure on protected areas from local communities interested in using the resources within the forest.

Within 10,000 meters of pinch point *B*, there are 307 respondents, and within 10,000 meters of pinch point *C,* there are 54 respondents. The average response on access to protected areas was 2.81 and 2.31 in pinch points *B* and *C*, respectively. Communities in both areas are fairly satisfied with their means to potentially benefit from protected areas. Good governance statements averaged 2.31 in pinch point *B* and 2.07 in pinch point *C*. Those patterns indicate moderately successful and productive relationships between governing bodies and the local groups (namely the CCC and local NGOs). Satisfaction with natural resource use averaged 2.3 in pinch point *B* and 2.01 in pinch point *C*.

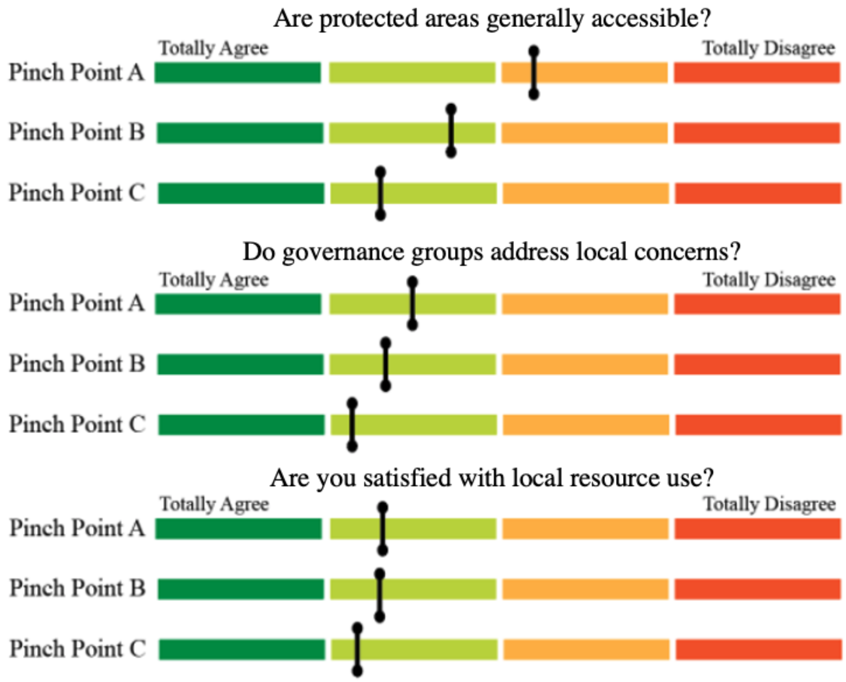

Figure 7. Average sentiment for households located within 10 kilometers of three pinch points for Grauer's gorilla movement on questions related to: access to protected areas, good governance, and local resource use.

Future Climate Scenarios

The mean AUC values for the montane and submontane models were greater than 0.9, indicating excellent model fit and prediction of these two vegetation types. We calculated an AUC of 0.701 for dense moist tropical forest. The lower AUC for dense moist tropical forest may be attributed to the broad extent of this vegetation type relative to the study extent rather than an indication of the insufficient predictive power of the model (Phillips, 2017). However, it may also indicate that the environmental variables used for this analysis do not fully describe the environmental conditions that determine dense moist forest distribution. We recommend further evaluation of the parameter and variable selection for Maxent and a sensitivity analysis to determine the relative effect of the study extent on the model's AUC.

Under the RCP 4.5 intermediate emission scenario, our analysis suggests that the extent of suitable habitat for gorillas will initially expand across the Sud-Kivu, Nord-Kivu, and Minema provinces, with an increase of 19% by the mid-century, but then decrease between 2050-2080 to an area only about 1.5% larger than the current extent. Montane, submontane, and dense moist forest coverage is predicted to increase between 7-36% depending on the vegetation type (*Table 4*) by 2050 but will decline by 13-16% by 2080. Submontane forest will lose around 6% of its current extent by 2080. No forest type was forecast to be stable under this climate scenario.

Two forest types, submontane and montane, are predicted to experience significant declines by 2080 under the RCP 8.5 emission scenario. As in the RCP 4.5 scenario, montane forest shows an initial increase in extent in 2050 but has a net loss of 24% by 2080. Submontane forest shows an accelerating decline throughout the century. Dense moist forest was the only vegetation type predicted to expand its range, with an estimated increase in area of 51%.

Table 4. The change in extent of each forest type predicted from the current and future distribution for four climate change scenarios under the RCP 4.5 intermediate emission scenario and RCP 8.5 high emission scenario included in the IPCC Fifth Assessment Report (AR5), extended to the years 2050 and 2080.

				RCP 4.5		
	Extent in 2020 km^2	Extent in 2050 km^2	Extent in 2080 km^2	% Change 2020-2050	% Change 2050-2080	Total Change 2020-2080
Montane	14641	19966	17200	36.37%	-13.85%	17.48%
Submontane	27519	29650	25749	7.74%	-15.18%	-6.43
Dense Moist Forest	84387	102115	85474	21.01%	-16.3%	1.29%
Total Forest Cover	126548	151731	128423	19.90%	-15.36%	1.48%

				RCP 8.5		
	Extent in 2020 km^2	Extent in 2050 km^2	Extent in 2080 km^2	% Change 2020-2050	% Change 2050-2080	Total Change 2020-2080
Montane	14641	17186	11125	17.38%	-35.37%	-24.01%
Submontane	27519	26386	21501	-4.12%	-18.51	-21.87%
Dense Moist Forest	84387	89665	127561	6.26%	42%	51.16%
Total Forest Cover	126548	133237	160187	5.29%	20.23%	26.58%

Montane Forest Climate Response

The spatial analysis for montane forest shows a general trend of suitable areas for this forest type shifting to the southern regions of the Sud-Kivu province under all four climate scenarios (*Figure 8*). On average, 73% of the present extent is stable under increased emission scenarios. All four scenarios predict a substantial loss of montane forest cover in the Nord-Kivu province, with areas of forest loss extending south into the eastern side of Kahuzi-Biega National Park under the 2070 RCP 8.5 scenario. The results show minor differences in the amount of area lost between the four scenarios (*Table 5*). Most of the gain in montane forest extent occurs around the area of Itombwe Nature Reserve, but the amount of suitable extent gained varies between the projected climate scenarios. Under RCP 8.5, there is between 35-87% less gain in montane forest extent compared to RCP 4.5, indicating that as greenhouse gas emissions increase, the extent of montane forest will decrease (*Table 5*).

Table 5. Projected gain and loss of area for montane forest shown in km^2 for 2050 and 2070 under the RCP 4.5 intermediate emission scenario and RCP 8.5 high emission scenario included in the IPCC Fifth Assessment Report (AR5).

	2050		2070	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Area Gained (km^2)	8994.62	5849.7	6265.19	1164.3
Area Lost (km^2)	3670.09	3291.04	3720.81	4680.4
Stable Area (km^2)	10971.31	11350.36	10920.58	9961

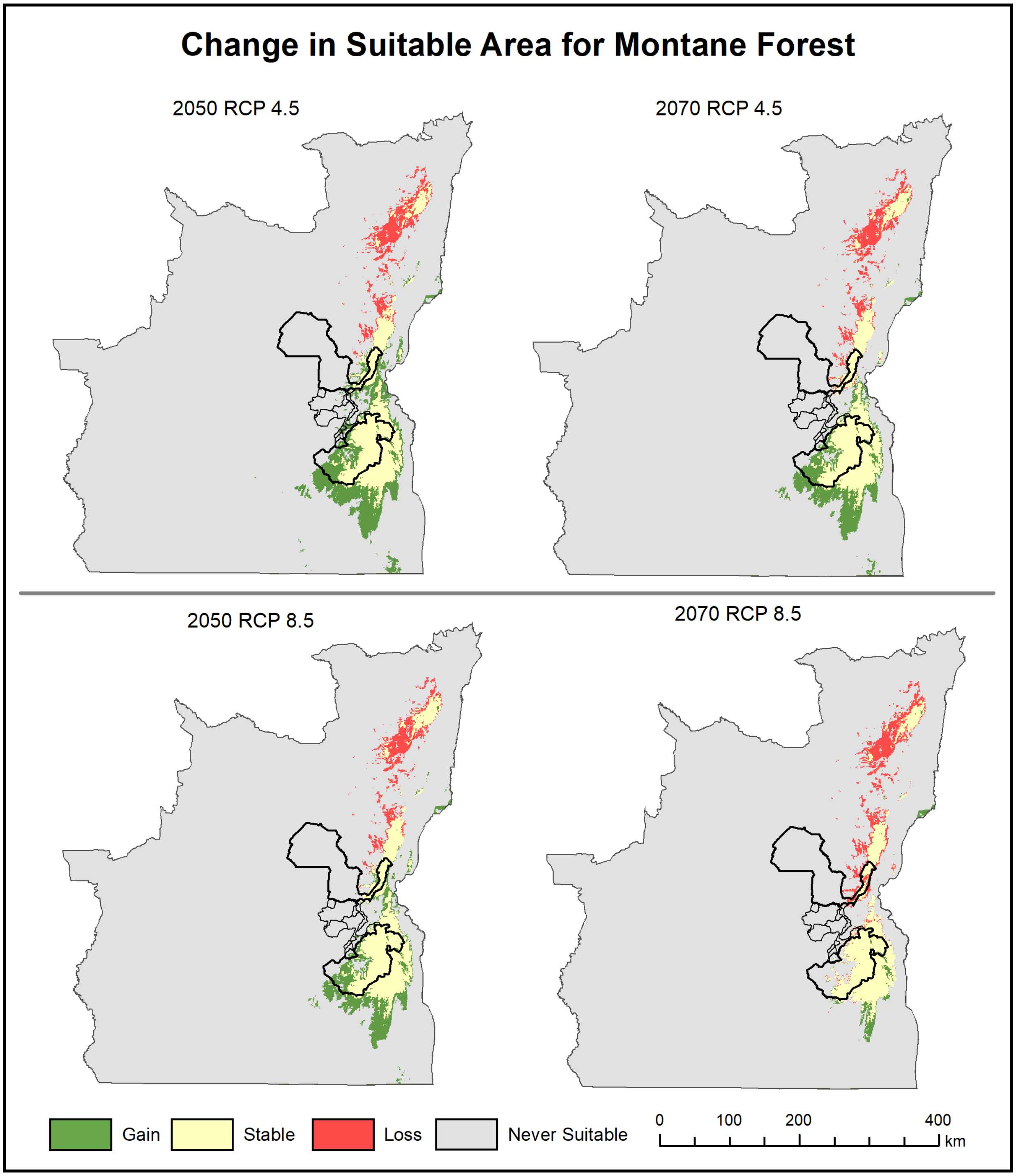

Figure 8. Projected change in montane forest extent for 2050 and 2070 under RCP 4.5 and RCP 8.5 greenhouse gas emission scenarios in the Sud-Kivu, Nord-Kivu, and Maniema provinces in the Democratic Republic of Congo. Gains in climatically suitable areas are shown in green and loss of suitable areas in red. Areas where no change is predicted between current and future extent are shown in yellow. Kahuzi-Biega National Park, Itombwe Nature Reserve, and Strong Roots community forest network are outlined in black, representing the area of concern for Grauer's gorilla conservation. Future extents are predicted based on consensus between 5 GCMs, CESMI-BGC, MPI-ESM-MR, ACCESS01, MICROC5, and CMCC-CM included in the IPCC Fifth Assessment Report (AR5).

Submontane Forest Climate Response

Submontane forest shows a general shift toward the east, losing 50% or more of the current extent (*Figure 9*). The average percentage of stable habitat decreased by 13% between the RCP 4.5 and RCP 8.5 scenarios (*Table 6*). The total loss of submontane forest within the provinces ranges from 47-72%, with losses increasing as greenhouse gas emissions increase. All four climate scenarios predict the substantial loss of submontane habitat within the boundaries of Kahuzi-Biega National Park, with an almost complete disappearance of this forest type by the end of the century under the RCP 8.5 scenario. A similar but less extreme trend of submontane forest loss is seen in the area between Kahuzi-Biega and Itombwe under all but the 2070 RCP 8.5 scenario, predicting a near-total loss of submontane forest in this region as well. Gains in submontane forest will mostly occur in the western regions of Sud and Nord-Kivu, and all four scenarios predict a similar amount of area gained. By the end of the century both RCP 4.5 and RCP 8.5 scenarios predict that more submontane forest area will be lost than is gained.

Table 6. Projected gain and loss of area for submontane forest shown in km^2 for 2050 and 2070 under the RCP 4.5 intermediate emission scenario and RCP 8.5 high emission scenario included in the IPCC Fifth Assessment Report (AR5).

	2050		**2070**	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Area Gained (km^2)	15113.69	13412.8	13350.99	13885.8
Area Lost (km^2)	12983.38	15183.36	14484.56	19904.13
Stable Area (km^2)	14536.01	12336.03	13034.82	7615.26

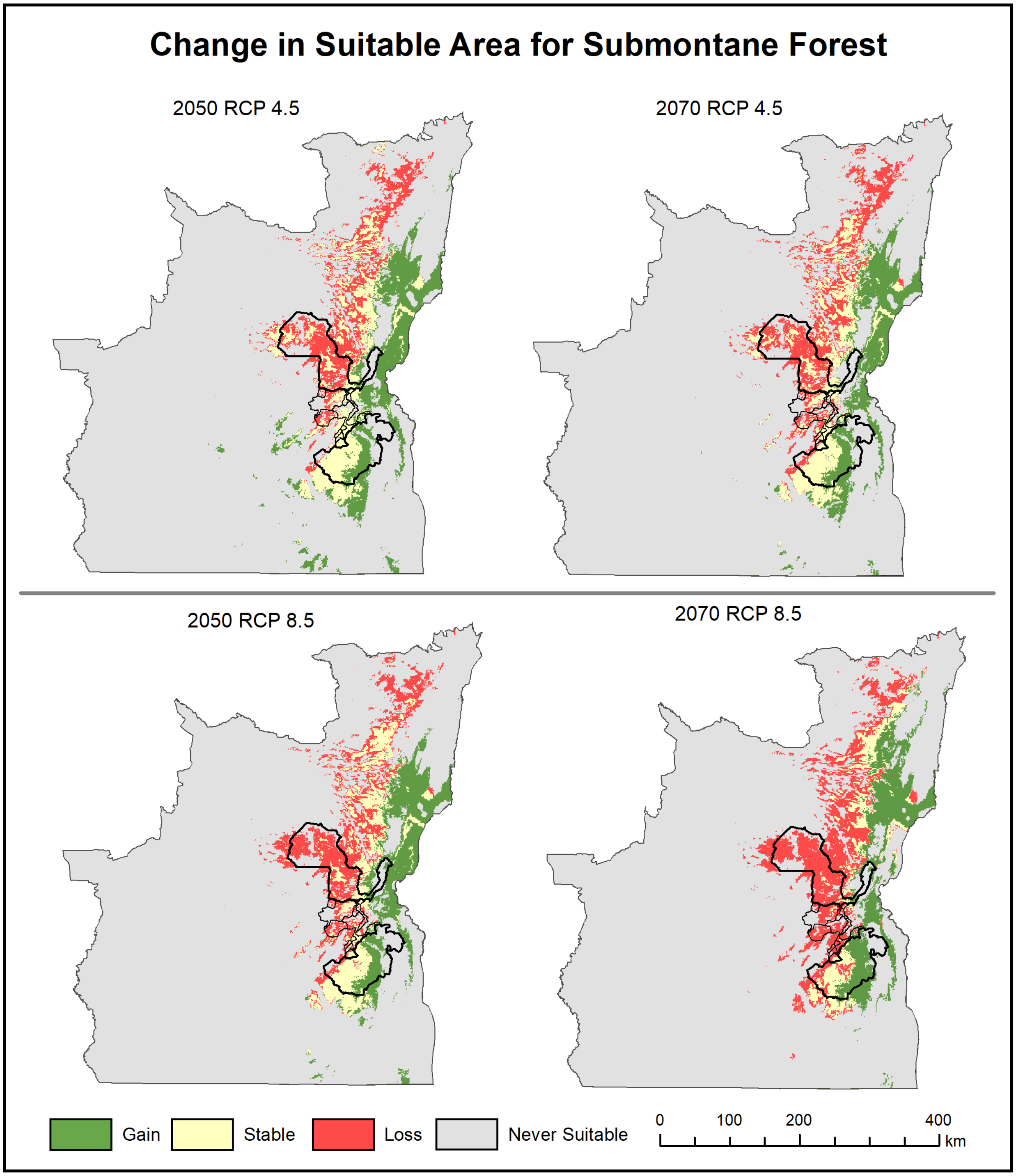

Figure 9. Projected change in submontane forest extent for 2050 and 2070 under RCP 4.5 and RCP 8.5 greenhouse gas emission scenarios in the Sud-Kivu, Nord-Kivu, and Maniema provinces in the Democratic Republic of Congo. Gains in climatically suitable areas are shown in green and loss of suitable areas in red. Areas where no change is predicted between current and future extent are shown in yellow. Kahuzi-Biega National Park, Itombwe Nature Reserve, and Strong Roots community forest network are outlined in black, representing the area of concern for Grauer's gorilla conservation. Future extents are predicted based on consensus between 5 GCMs,

CESMI-BGC, MPI-ESM-MR, ACCESS01, MICROC5, and CMCC-CM included in the IPCC Fifth Assessment Report (AR5).

Moist Dense Forest Climate Response

The spatial analysis of dense moist forest shows that this forest type is predicted to be the most stable under all climate change scenarios (*Figure 10*). An average of 90% of the current extent is predicted to be stable as greenhouse gas emissions increase (*Table 7*). Dense moist tropical forest is the only forest type to show substantial gains in extent under the RCP 8.5 high emission scenario. The majority of these gains occur in the southwestern region of Maniema. However under RCP 8.5, our model predicts a substantial increase in dense moist forest extent into the northern part of Kahuzi-Biega and the western part of Itombwe by the end of the century. The gains in dense tropical forest in both parks overlap with areas of submontane forest loss indicating that submontane forest may be replaced by dense moist tropical forest within the current range of Grauer's gorillas.

Table 7. Projected gain and loss of area for dense moist tropical forest shown in km^2 for 2050 and 2070 under the RCP 4.5 intermediate emission scenario and RCP 8.5 high emission scenario included in the IPCC Fifth Assessment Report (AR5).

	2050		**2070**	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Area Gained (km^2)	24323.74	14458.84	15726.74	44570.45
Area Lost (km^2)	6595.29	13371.71	10448.29	1336.49
Suitable Area (km^2)	77791.3	71014.88	73938.66	83050.09

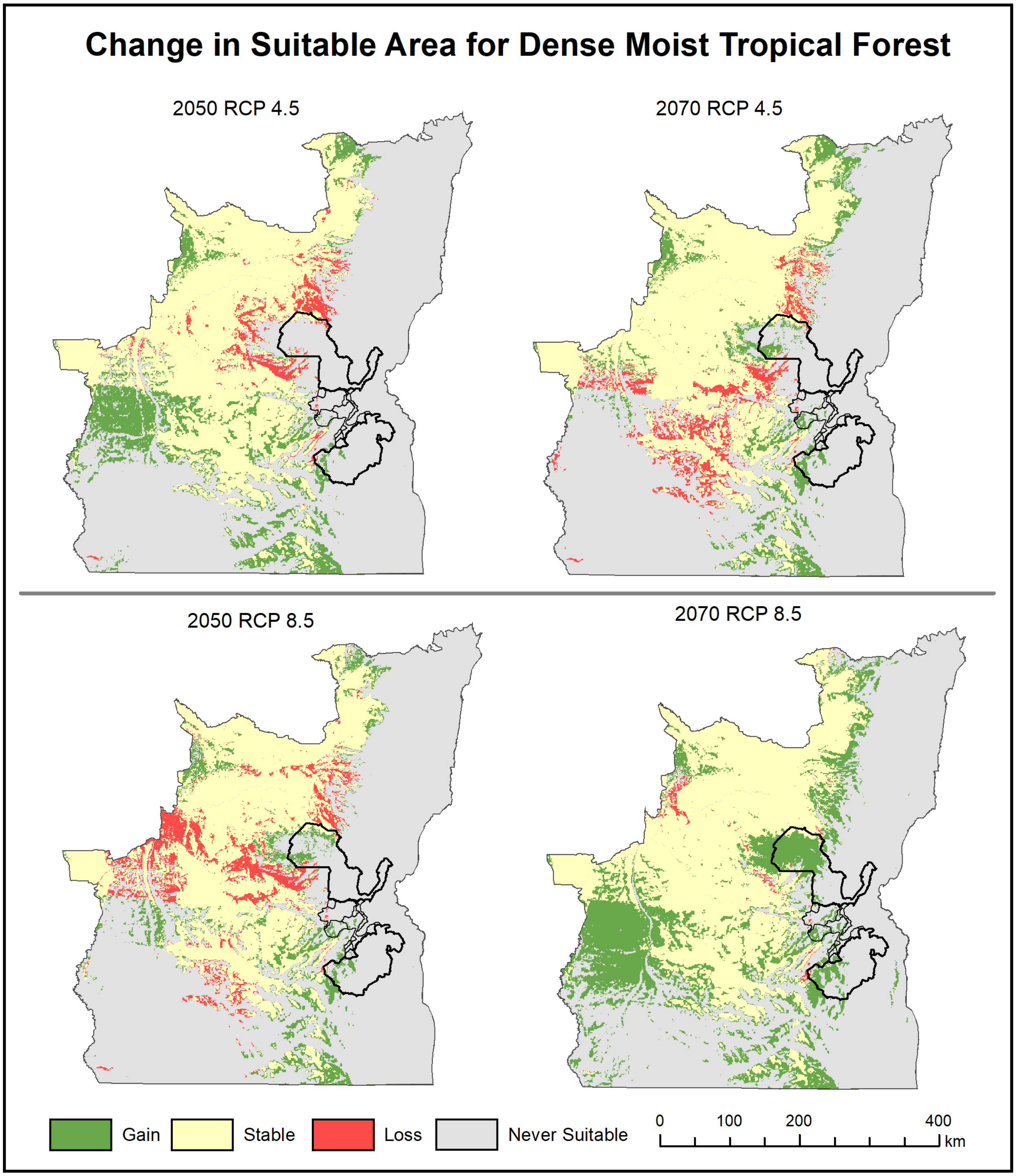

Figure 10. Projected change in dense moist tropical forest extent for 2050 and 2070 under RCP 4.5 and RCP 8.5 greenhouse gas emission scenarios in the Sud-Kivu, Nord-Kivu and Maniema provinces in the Democratic Republic of Congo. Gains in climatically suitable areas are shown in green and loss of suitable areas in red. Areas where no change is predicted between current and future extent are shown in yellow. Kahuzi-Biega National Park, Itombwe Nature Reserve, and Strong Roots community forest network are outlined in black, representing the area of concern for Grauer's gorilla conservation. Future extents are predicted based on consensus between 5 GCMs, CESMI-BGC, MPI-ESM-MR, ACCESS01, MICROC5, and CMCC-CM included in the IPCC Fifth Assessment Report (AR5).

Habitat Resilience

The resilience analysis identifies areas where current and future forest habitats are predicted to overlap under different climate scenarios. These areas are of particular importance for conservation because they provide both current and future benefits to Grauer's gorillas and can serve as a "bridge" for gorillas responding to the shifts in forest extent predicted by the previous models. Our results show very few areas of resilience within Kahuzi-Biega National Park and in the northeastern region of the corridor. The majority of the Itombwe Nature Reserve is resilient under all four climate scenarios (*Figure 11*).

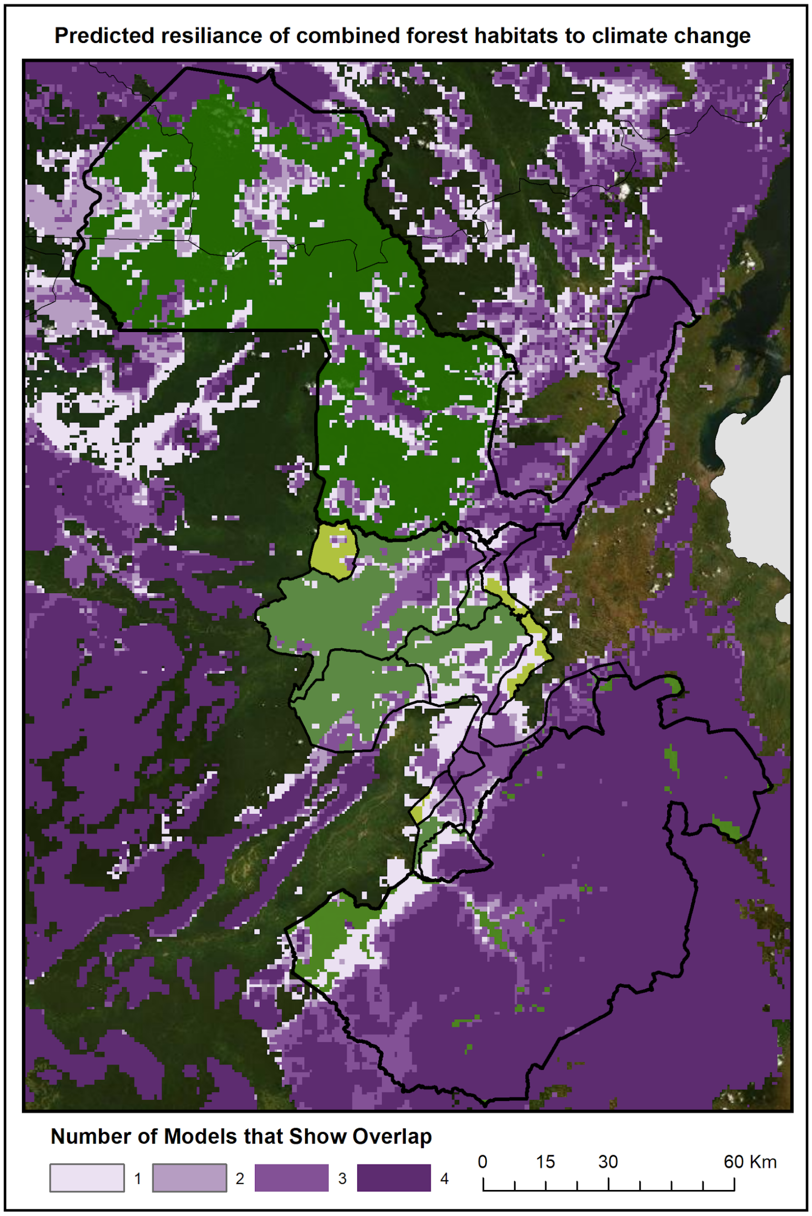

Figure 11. Areas of Grauer's gorilla habitat predicted to be most resilient to climate change. Overlap areas for all three forest types are combined to show the total extent of gorilla habitat predicted to be resilient to climate change. The numbers in the legend indicate how many climate change scenarios identified that area as having overlap between the current and future distribution.

Discussion

Conservation Need Assessment

The main findings of the deforestation assessment across community forests throughout the DRC indicate that this management strategy has not yet effectively reduced local deforestation compared to non-protected areas. However, these results can likely be attributed to the current novelty of CBFM in the DRC, where the first community forest was fully established in early 2017. Regardless, the lack of short-term solutions to deforestation in these CF areas indicates that land grants alone will not reverse deforestation impacts in the DRC. Additional interventions are necessary for these areas to target deforestation specifically. This could include enforcement against illegal logging and extraction quotas to prevent excessive logging, in combination with reforestation efforts like tree planting initiatives.

The results also show that the Sud-Kivu study region is experiencing higher deforestation rates compared to the rest of the country. Thus, it is critical to implement strong management practices in this area to protect the many endemic species that rely on the primary rainforest of the central-eastern DRC for habitat from extinction.

Connectivity, Pinch Points & Potential Barriers

Modeling connectivity has become a key method in conservation planning to quantify species movement and identify critical areas for conservation and restoration. However, many organizations, such as Strong Roots Congo, do not have access to the modeling and GIS technology required for the analysis. We performed a connectivity analysis for Strong Roots to inform (1) priority areas for current conservation and (2) key areas where they should prioritize restoration activities.

The connectivity and pinch point analyses allowed us to identify key locations that should be prioritized for habitat conservation within the community forest network. Only one of the three identified pinch points is within the proposed corridor boundaries. The two pinch points outside of the proposed boundaries are not under the protection of Strong Roots. Currently, the conservation of the small section of the proposed corridor that bottlenecks between the respective northern and southern portions is the most vital to Grauer's gorilla connectivity between Kahuzi-Biega National Park and Itombwe Nature Reserve. The high connectivity areas within the corridor, especially those along the least-cost path, are a second priority for conservation efforts. The protection of this highly suitable habitat will facilitate Grauer's gorilla persistence and movement within the corridor. The conservation of both pinch points and areas of high connectivity in the corridor will allow Grauer's gorillas to safely and successfully travel through and reside in the Kahuzi-Biega-Itombwe corridor.

The barrier analysis allowed us to identify three proposed reforestation zones to prioritize reforestation efforts to reduce barriers to movement for Grauer's gorillas in the Kahuzi-Biega-Itombwe corridor. Partial barriers are defined as a land type that could feasibly be converted to established secondary forest habitat, such as abandoned agricultural land or previously cleared land (McRae et al., 2012), and thus have high restoration potential. The identified barriers appear to be partial barriers of slightly fragmented forests that do not contain permanent impermeable features such as settlements. The lack of permanent barrier features and lack of competing land use mean these areas have a high potential to be converted back into intact forest habitat. The location of these barriers within proposed restoration zones is beneficial to Strong Roots' simultaneous goals of reducing deforestation and improving Grauer's gorilla connectivity. The restoration of these areas by Strong Roots will significantly improve overall Grauer's gorilla connectivity across the corridor by reducing the cost of movement through the landscape. Reforestation efforts in these locations specifically will create more highly suitable habitat within the corridor which will make it easier for gorillas to travel through and persist.

Limitations

Resistance models that primarily rely on expertise knowledge need to be produced with careful consideration of biological processes and are not substitutes for empirically-based models (Zeller et al., 2012; Wade et al., 2015). In modeling connectivity for Grauer's gorilla populations, data limitations may hinder the robustness of the results. The environmental needs of Grauer's gorillas have been poorly studied, which makes the ecological requirements of the species uncertain. Within the Circuitscape analysis, a fundamental assumption is that habitat suitability is synonymous with permeability and that both are the inverse of travel cost. This assumption is based on two principles. The first is that habitat suitability is the same as habitat permeability—the more suitable habitat is for survival, growth, and reproduction, the easier it is for the organism to move through (Singleton & McRae, 2013). Second, permeability is the inverse of energetic movement cost—the easier it is to move through an area (high permeability), the less energy it takes for an organism to move through. The lack of empirical data on Grauer's gorilla movement makes these principal assumptions difficult to test (Koen et al., 2010). Future research on gorilla movement, dispersal behavior, and their relationship to landscape features would improve the robustness of this analysis.

Community Wellbeing & Opinions

The proximity analysis results are useful for determining where to focus development and educational outreach activities. In the study area, the creation of both existing protected areas, Kahuzi-Biega and Itombwe, has been criticized for failing to yield real management responsibilities to local communities and aiding in indigenous groups' displacement. Residents feel that the governing bodies remain in an authoritative position that undermines community forestry's goals and intent: empowering local groups with the onus to manage their own forest resources effectively. Protected areas in this region have provided ecological benefits, but concern remains whether actual welfare benefits can be derived from community forestry. This mistrust creates an environment where there is the possibility that lack of community engagement could undermine the successful implementation of CBFM.

The sentiments that coincide with distance to the protected area inform our client about their efforts to make the most impact both geographically and strategically. We found that lack of access to the forest could hinder the success of CBFM in the Sud-Kivu region. We determined that communities furthest from the Itombwe Nature Reserve have generally greater dissatisfaction with community forestry's efforts, as they have not directly experienced the touted benefits. This could be the result of these communities not having access to the resources available within the forest. According to survey responses, their sentiments are rooted in a lack of vehicular access to Itombwe Nature Reserve and unpleasant experiences with the CCC (Community Conservation Committee). Exploring current attitudes toward community forestry in the areas near pinch points indicates that two of the three communities somewhat agree with the need and importance of conservation but indicate that there are opportunities to improve local support in these critical areas.

In the future, as CBFM plans are finalized, Strong Roots will be able to observe how sentiments begin to change. Ideally, Strong Roots and governing groups would like to see widespread agreement and statewide satisfaction with CBFM since studies of successful CF efforts indicate greater local engagement increases community benefits rooted in co-management (Charnley & Poe, 2007). Flexibility in this data exploration will be useful as boundaries of protected areas change, community forests are decreed, and future social studies are refined.

Future Climate Scenarios

Projections on how climate change will alter viable gorilla habitat can help target conservation strategies to ensure that resilient future habitat and connectivity points remain intact. Significant shifts are predicted in the primary forest types of gorilla habitat, and there is considerable uncertainty associated with the extent and spatial distribution of future habitat. This makes identifying areas where future habitat overlaps with current habitat under multiple climate change scenarios an important conservation consideration for developing a climate resilient management strategy (Glick et al., 2011). Allocating resources to these overlap areas will not only protect connectivity between the protected areas in the current landscape but help facilitate gorilla movement to suitable habitat in the future. This is particularly important to consider as our resilience model indicates that Kahuzi-Biega National Park has very low resilience and is likely to experience large contractions in the extent of gorilla habitat within its borders. Extensive loss of habitat in the park could potentially result in the extinction of the Kahuzi-Biega sub-population if Grauer's gorillas cannot disperse outside of the park to respond to this loss of suitable habitat. The potential loss of the Kahuzi-Biega core population could be catastrophic for the long-term persistence of the species. Ensuring that areas of future suitable habitat outside of the park are available for Grauer's gorillas to disperse into may be critical to prevent the local extinction of this sub-population and the resulting loss of genetic diversity in the species.

Our results also indicate that the majority of Itombwe is predicted to have overlap between current and future gorilla habitat under all four climate scenarios, meaning that this area could serve as a potential refugium for the species. Safeguarding connectivity between the parks can thus create an 'escape route' into a large area of protected habitat should a worst-case climate scenario occur, which would result in the disappearance of Grauer's gorilla habitat in Kahuzi-Biega.

Limitations and Next Steps

The selection of environmental variables and Maxent parameters can have a notable impact on model performance (Zeng et al., 2016). Optimization of the input parameters and environmental variables for this analysis is outside the scope of this study because it requires a considerable amount of time and computational power. Future testing of the optimal Maxent settings could produce more accurate future distribution models, especially for dense moist forest which had the lowest AUC. A sensitivity analysis of the selected threshold value used to create the binary presence estimates would also improve the robustness of this analysis. Future research into the impact of climate change for Grauer's gorillas should aim to understand the likely temporal rates of habitat shifts and the likelihood of successful adaptation to new climatic conditions for the forest vegetation that gorillas rely on.

Conclusion

Study Relevance

This project contributes to the knowledge of current and future Grauer's gorilla habitat connectivity in the Sud-Kivu region and highlights how community opinions on conservation in the region are dependent on the benefit community members receive from the protected land. Our connectivity evaluation has identified pinch points and barriers to Grauer's gorilla movement in the corridor between Kahuzi-Biega National Park and Itombwe Nature Reserve. Pinch points and areas identified as having high connectivity value along the least-cost path are a high conservation priority. Additional high connectivity value pathways can be examined for conservation feasibility based on community stakeholder input. Identification of barrier locations assists Strong Roots in directing restoration efforts to these areas. Additionally, the location of priority restoration areas combined with the assessment of community opinions will allow Strong Roots to target outreach efforts and provide educational materials on conservation plans to these communities. Furthermore, we have identified areas of data limitations in our results to help Strong Roots and other NGOs working in the area direct future studies and research to close those knowledge gaps. The deliverables containing current connectivity and future habitat predictions, community opinions, and the data limitations within each, will provide Strong Roots with a comprehensive analysis of Grauer's gorilla connectivity in the Sud-Kivu region and allow them to develop a management plan for the community forest. Through targeted conservation efforts and directed community outreach, Strong Roots and participating chiefdoms within the region can help promote connectivity and community wellbeing to increase Grauer's gorilla populations.

Strong Roots Congo is not alone in its mission to improve biodiversity and community livelihoods throughout the DRC. While this project considers the implications of CBFM within the Sud-Kivu study region, biodiversity and local community needs extend past our study boundary. In the coming years, it will become increasingly important for adjacent CFs to assist NGOs and communities in aligning conservation efforts and allow for the full connection of the remaining Grauer's gorilla populations. The Grauer's gorilla sub-population centered out of Kahuzi-Biega frequently travels north, out of the study region and toward Nord-Kivu and Maiko National Park, which is home to two more sub-populations. In the Nord-Kivu region, several CFs, assisted primarily by WWF, have been established, however, the protected areas in this region are not currently managed as a cohesive network. We hope our findings will serve as a framework for developing a climate-wise corridor network between Nord-Kivu and Kahuzi-Biega.

Recommendations

The models we developed provide an insight into Grauer's gorilla connectivity in the context of a changing climate and community opinions on conservation in the area. They have the potential to be adjusted and applied to other habitat connectivity corridors in the area, specifically the Kahuzi-Biega-Maiko corridor. Our models can guide conservation planning to identify priority areas that should be off-limits to resource extraction and where sustainable development can occur that would least impact focal species. At a minimum, we recommend ensuring the corridor along the least-cost path between the parks and the associated pinch points be prioritized for conservation. Areas of gorilla habitat that have both high connectivity and climate resilience within the corridor should also be considered for protection to create a connected network of refugia patches that will continue to facilitate movement in the future. We also recommend that Strong Roots use our model results as supplementary materials in the application to the DRC government for community-based forest management of the region.

The identified pinch point located within the proposed corridor boundaries should be considered for immediate and ongoing conservation management by Strong Roots. The pinch point identified within the proposed corridor boundaries is a critical link in connectivity and should be the key focus for conservation efforts and budget. Strong Roots should also consider the potential to expand the community forest boundaries to protect the two additional pinch points identified in this analysis.

We suggest prioritizing the identified barriers within the reforestation zones for the first restoration efforts by Strong Roots. These areas should be investigated on the ground level to identify the source of the barrier and the potential for restoration (McRae et al., 2012). If a barrier has high restoration potential, we recommend cross-referencing barrier locations with the climate model to determine the area's predicted resistance to climate change. If the area is not resistant to climate change, tree planting may be unsuccessful as a long-term solution. If the area is resistant to climate change, plans to restore the barrier should focus on the projected forest type under climate scenarios, rather than attempting to restore a historical forest type that would no longer be suitable in the region.

The pinch point sentiment analysis results, in combination with the information gained from the socioeconomic survey, should be used to guide the prioritization of developmental and educational activities in neighboring communities. Those living near the pinch points felt generally dissatisfied and disengaged with current conservation efforts. Since CBFM has been shown to be more successful with directed community conservation education (Gilmour, 2016), it is important to target these sub-communities for outreach. The findings should help communicate conservation efforts and identify ways to meaningfully engage with the local community to remedy specific criticisms of community forestry.

While the combination of our connectivity and climate projection models highlights the achievable conservation benefits if key pinch-point areas are safeguarded, the socioeconomic model indicates that our analysis and the data provided was not enough to determine direct community opinions on CBFM. We suggest that surveys be carried out annually to directly assess community opinion and concerns regarding the CF corridor as protected forest boundaries expand and more areas are declared (Urech et al., 2013). Questions assessing community opinions on CF creation and management and quantifying forest resource collection in the newly implemented CF would allow for deeper insight into community opinions on the CF and allow management strategies to address those opinions. We also believe that a refined survey must include targeted free response questions and in-depth participant evaluations to allow for more detailed feedback. Performing a standard survey consistently will make information available to determine whether there are substantial changes in wellbeing outcomes and attitudes over a period of time.

The climate analysis revealed that tropical dense moist forest habitat in the north end of the corridor into Kahuzi-Biega National Park is not expected to be resilient to climate change. These findings emphasize the need for a connection between Grauer's gorilla sub-populations residing in Kahuzi-Biega National Park and Maiko National Park. As shifts in climate make these regions unsuitable for dense moist forest, the region will likely serve as an evacuation corridor.

Even taken as a whole, these findings are not intended to prescribe specific day-to-day management strategies in the corridor. Rather, the ecological conditions of the corridor and potential obstacles produced from the models should serve as guidance for management decisions that could maximize benefits to all stakeholders and enhance landscape longevity in the face of climate change. We are honored to have collaborated with Strong Roots Congo on this project and look forward to seeing the benefits that the proposed community forest corridor will bring to local biodiversity and communities.

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Appendix

Appendix A: Conservation Need Assessment

A.1 Figures and Data Acquisition

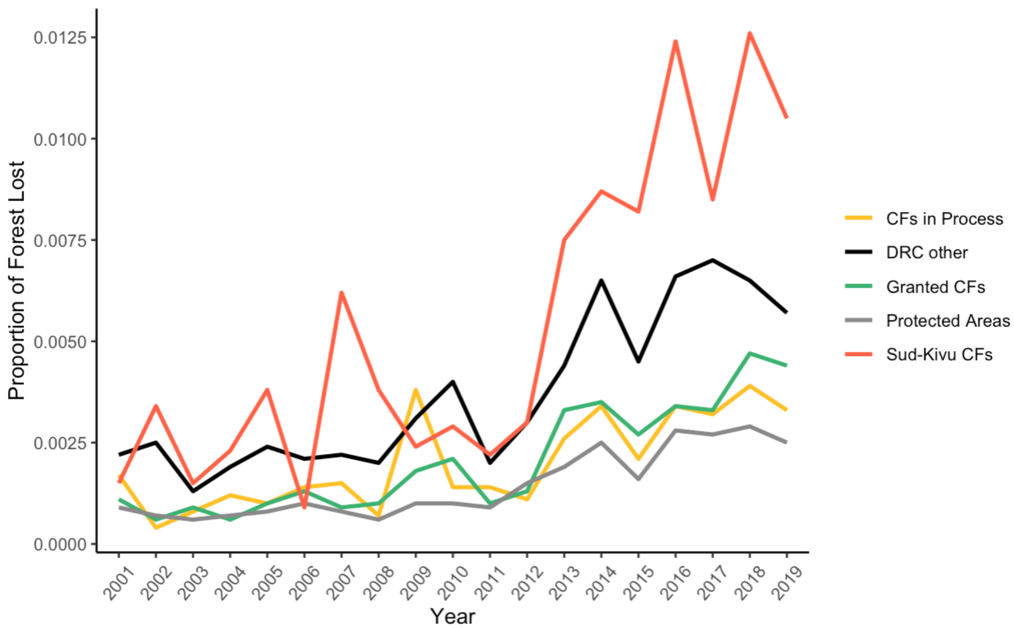

Figure A.1.i. Proportional forest loss in the DRC from 2001-2019. The proportion of forest lost annually for 5 zones of different protection status: granted community forests in green, community forests in the process of being granted in yellow, other protected areas in gray, the Sud-Kivu community forest corridor in red, and all other non-protected areas in the DRC in black.

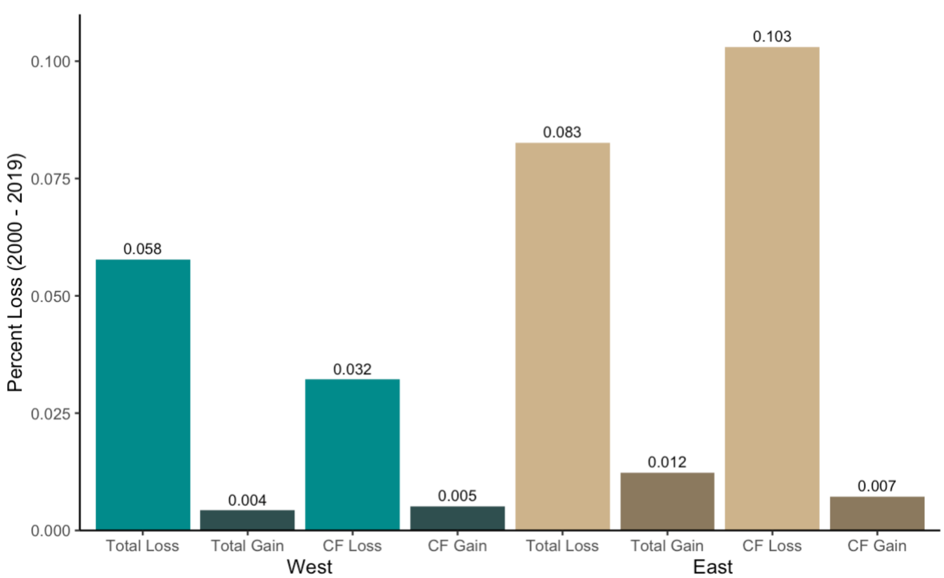

Figure A.1.ii. Percent forest loss and gain by east and west DRC. The total proportional forest loss and gain by area from 2000 to 2020 in the eastern and western DRC provinces that have CFs present and the total proportional forest loss and gain within the CFs in the east and western provinces.

Table A.1.i. Data Acquisition for the conservation need assessment, including the data type, source, description and projection and datum.

Variable	Source	Data Type	Description	Projection & Datum
loss	Global Forest Watch	Raster	Forest loss during the study period, defined as a stand-replacement disturbance (a change from a forest to non-forest state).	WGS_1984 unprojected
lossyear	Global Forest Watch	Raster	Forest loss during the period 2000–2019, defined as a stand-replacement disturbance, or a change from a forest to non-forest state. Encoded as either 0 (no loss) or else a value in the range 1–17, representing loss detected primarily in the year 2001–2019, respectively.	WGS_1984 unprojected
gain	Global Forest Watch	Raster	Forest gain during the period 2000–2019, defined as the inverse of loss, or a non-forest to forest change entirely within the study period. Encoded as either 1 (gain) or 0 (no gain).	WGS_1984 unprojected
DRC country shape	WRI	Geodatabase features .shp file of African countries	The country shape of the DRC	GCS_Clarke_1880 unprojected
CFs in DRC shape	WRI	Geodatabase features .shp files of Community Forests in DRC	The shape of several community forests in the DRC	GCS_Clarke_1880 unprojected
Additional CFs in DRC shape	Scraped from Rainforest UK Mapping for Rights	Geodatabase features .shp files of Community Forests in DRC	The shape of all community forests in the DRC	GCS_Clarke_1880 unprojected
Protected areas in DRC shape	WRI	Geodatabase features .shp files of the Protected areas in DRC	The shape of all protected areas in the DRC	GCS_Clarke_1880 unprojected
Network area	Strong Roots Congo	.shp file for network area	The shape of the target network area	WGS_1984_UTM_Zone_35S

A.2 Prepare Data in Google Earth Engine: Upload datasets, polygons, and assets to create Zones (DRC, CFs, PAs):

```
// Load Zones: (1) Democratic Republic of the Congo, (2a) all Community Forests, (2b) Granted Community Forests, (2c) Application in Process Community Forests, (3) Sud-Kivu Community Forest, and (4) Protected Areas.

 // (1) Load country features from Large Scale International Boundary (LSIB) dataset.
 var countries = ee.FeatureCollection('USDOS/LSIB_SIMPLE/2017');

          // Subset the DRC feature from countries variable.
          var DRC = ee.Feature(
           countries.filter(ee.Filter.eq('country_co', 'CG')).first()
          );

 // (2a) Load Community Forest polygons from assets.
 var allCF = ee.FeatureCollection(all_CF)

 // (2b) Subset Granted Community Forest polygons from assets.
 var GNT = ee.FeatureCollection(all_CF)
  .filter(
   ee.Filter.inList('Status', ['Granted']));

 // (2c) Subset Application in Process Community Forest polygons from assets.
 var AIP = ee.FeatureCollection(all_CF)
  .filter(
   ee.Filter.inList('Status', ['Application in Process']));

 // (3) Load Sud-Kivu Community Forest polygons from assets.
 var SK = ee.FeatureCollection(all_CF)
  .filter(
   ee.Filter.inList('Name', ['Sud_Kivu']));

 // (4) Load Protected Area features from shapefiles.
 var PA = ee.FeatureCollection(protected_areas);

// Load Global Hansen dataset.
var gfc2019 = ee.Image('UMD/hansen/global_forest_change_2019_v1_7');
```

A.3 Prepare Data: Map and clip zones to tree cover bands (loss + gain):

```
// Get the loss and gain image layers.
var lossImage = gfc2019.select(['loss']);
var areaLOSSImage = lossImage.multiply(ee.Image.pixelArea());
var gainImage = gfc2019.select(['gain']);
var areaGAINImage = gainImage.multiply(ee.Image.pixelArea());

// Calculate loss in zones.

 // (1) DRC loss.
 var lossDRC = areaLOSSImage.reduceRegion({
          reducer: ee.Reducer.sum(), geometry: DRC.geometry(), scale: 30, maxPixels: 1e10});
 print('DRC LOSS TOTAL: ', lossDRC.get('loss'), 'square meters');
 // (2a) CF loss.
 var lossCF = areaLOSSImage.reduceRegion({
          reducer: ee.Reducer.sum(), geometry: allCFALL.geometry(), scale: 30, maxPixels: 1e10});
 print('DRC LOSS TOTAL: ', lossCF.get('loss'), 'square meters');
 // (2b) CF loss.
 var lossGNT = areaLOSSImage.reduceRegion({
```

```
		reducer: ee.Reducer.sum(), geometry: GNT.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', lossGNT.get('loss'), 'square meters');
// (2c) CF loss.
var lossAIP = areaLOSSImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: AIP.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', lossAIP.get('loss'), 'square meters');
// (3) SK loss.
var lossSK = areaLOSSImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: SK.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', lossSK.get('loss'), 'square meters');
// (4) PA loss.
var lossPA = areaLOSSImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: PA.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', lossPA.get('loss'), 'square meters');


// (1) DRC gain.
var gainDRC = areaGAINImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: DRC.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', gainDRC.get('gain'), 'square meters');
// (2a) CF gain.
var gainCF = areaGAINImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: allCFALL.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', gainCF.get('gain'), 'square meters');
// (2b) CF gain.
var gainGNT = areaGAINImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: GNT.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', gainGNT.get('gain'), 'square meters');
// (2c) CF gain.
var gainAIP = areaGAINImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: AIP.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', gainAIP.get('gain'), 'square meters');
// (3) SK gain.
var gainSK = areaGAINImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: SK.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', gainSK.get('gain'), 'square meters');
// (4) PA gain.
var gainPA = areaGAINImage.reduceRegion({
		reducer: ee.Reducer.sum(), geometry: PA.geometry(), scale: 30, maxPixels: 1e10});
print('DRC LOSS TOTAL: ', gainPA.get('gain'), 'square meters');

// (1) DRC area.
var DRCarea = DRC.geometry().area();
var DRCareaSqM = ee.Number(DRCarea);
print('DRC AREA:', DRCareaSqM, 'square meters');
// (2a) CF area.
var CFarea = allCF.geometry().area();
var CFareaSqM = ee.Number(CFarea);
print('CF AREA:', CFareaSqM, 'square meters');
// (2b) GNT area.
var GNTarea = GNT.geometry().area();
var GNTareaSqM = ee.Number(GNTarea);
print('GNT AREA:', GNTareaSqM, 'square meters');
// (2c) AIP area.
var AIParea = AIP.geometry().area();
var AIPareaSqM = ee.Number(AIParea);
print('AIP AREA:', AIPareaSqM, 'square meters');
// (3) SK area.
var SKarea = SK.geometry().area();
var SKareaSqM = ee.Number(SKarea);
print('SK AREA:', SKareaSqM, 'square meters');
```

```
// (4) PA area.
var PAarea = PA.geometry().area();
var PAareaSqM = ee.Number(PAarea);
print('PA AREA:', PAareaSqM, 'square meters');
```

A.4 Calculate Deforestation: Deforestation Rates and Loss Per Year, 2001-2019:

```
var total = 0;
var year;
var ID;

//all DRC lossyear loop
var ly_DRC_output = [];
for(year=1; year<20; year++) {
  var DRC_ly = gfc2019.select(['lossyear']).eq(year);
  var areaDRC_ly = DRC_ly.multiply(ee.Image.pixelArea());
  var statsDRC_ly = areaDRC_ly.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: DRC.geometry(),
    scale: 30,
    maxPixels: 1e10
  });
  var print_DRC_ly = 2000 + year;
  ly_DRC_output.push(ee.Feature(null, {'year':print_DRC_ly, 'lossyear':statsDRC_ly.get('lossyear')}));
}

var DRC_lossyear = ee.FeatureCollection(ly_DRC_output);

Export.table.toDrive({
  collection: DRC_lossyear,
  description: 'DRC_lossyear',
  fileFormat: 'CSV'
});

//all Protected Area lossyear loop
var ly_PA_output = [];
for(year=1; year<20; year++) {
  var PA_ly = gfc2019.select(['lossyear']).eq(year);
  var areaPA_ly = PA_ly.multiply(ee.Image.pixelArea());
  var statsPA_ly = areaPA_ly.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: PA.geometry(),
    scale: 30,
    maxPixels: 1e10
  });
  var print_PA_ly = 2000 + year;
  ly_PA_output.push(ee.Feature(null, {'year':print_PA_ly, 'lossyear':statsPA_ly.get('lossyear')}));
}

var PA_lossyear = ee.FeatureCollection(ly_PA_output);

Export.table.toDrive({
  collection: PA_lossyear,
  description: 'PA_lossyear',
  fileFormat: 'CSV'
});

//all CF GRANTED lossyear loop
```

```
var ly_GNT_output = [];
for(year=1; year<20; year++) {
  var GNT_ly = gfc2019.select(['lossyear']).eq(year);
  var areaGNT_ly = GNT_ly.multiply(ee.Image.pixelArea());
  var statsGNT_ly = areaGNT_ly.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: GNT.geometry(),
    scale: 30,
    maxPixels: 1e10
  });
  var print_GNT_ly = 2000 + year;
  ly_GNT_output.push(ee.Feature(null, {'year':print_GNT_ly, 'lossyear':statsGNT_ly.get('lossyear')}));
}

var GNT_lossyear = ee.FeatureCollection(ly_GNT_output);

Export.table.toDrive({
  collection: GNT_lossyear,
  description: 'GNT_lossyear',
  fileFormat: 'CSV'
});

//all CF APPLICATION IN PROCESS lossyear loop
var ly_AIP_output = [];
for(year=1; year<20; year++) {
  var AIP_ly = gfc2019.select(['lossyear']).eq(year);
  var areaAIP_ly = AIP_ly.multiply(ee.Image.pixelArea());
  var statsAIP_ly = areaAIP_ly.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: AIP.geometry(),
    scale: 30,
    maxPixels: 1e10
  });
  var print_AIP_ly = 2000 + year;
  ly_AIP_output.push(ee.Feature(null, {'year':print_AIP_ly, 'lossyear':statsAIP_ly.get('lossyear')}));
}

var AIP_lossyear = ee.FeatureCollection(ly_AIP_output);

Export.table.toDrive({
  collection: AIP_lossyear,
  description: 'AIP_lossyear',
  fileFormat: 'CSV'
});

// SUD-KIVU lossyear loop
var ly_SK_output = [];
for(year=1; year<20; year++) {
  var SK_ly = gfc2019.select(['lossyear']).eq(year);
  var areaSK_ly = SK_ly.multiply(ee.Image.pixelArea());
  var statsSK_ly = areaSK_ly.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: SK.geometry(),
    scale: 30,
    maxPixels: 1e10
  });
  var print_SK_ly = 2000 + year;
  ly_SK_output.push(ee.Feature(null, {'year':print_SK_ly, 'lossyear':statsSK_ly.get('lossyear')}));
}

var SK_lossyear = ee.FeatureCollection(ly_SK_output);
```

```
Export.table.toDrive({
  collection: SK_lossyear,
  description: 'SK_lossyear',
  fileFormat: 'CSV'
});
```

A.5 Calculate Deforestation: Regional Deforestation and Reforestation Rates:

```
// Generate regional zones: Central East & Central West.
        // East provinces and community forests.
        var East_Provs = ee.FeatureCollection(East_Provinces)
        var East_CF = ee.FeatureCollection(all_CF)
          .filter(
            ee.Filter.inList('province', ['Maniema', 'Ituri', 'Tshopo','Sud-Kivu']));

        // West provinces and community forests.
        var West_Provs = ee.FeatureCollection(West_Provinces)
        var West_CF = ee.FeatureCollection(all_CF)
          .filter(
            ee.Filter.inList('province', ['Équateur', 'Tshuapa', 'Mai-Ndombe','Kwilu']));

// Loss.
        // East
                // Provinces
                var loss_E_prov = areaLOSSImage.reduceRegion({
                        reducer: ee.Reducer.sum(), geometry: East_Provs.geometry(), scale: 30, maxPixels: 1e10});
                print('EAST PROVINCES LOSS: ', loss_E_prov.get('loss'), 'square meters');
                // Community Forest
                var loss_E_CF = areaLOSSImage.reduceRegion({
                        reducer: ee.Reducer.sum(), geometry: East_CF.geometry(), scale: 30, maxPixels: 1e10});
                print('EAST CF LOSS: ', loss_E_CF.get('loss'), 'square meters');
        // West
                // Provinces
                var loss_W_prov = areaLOSSImage.reduceRegion({
                        reducer: ee.Reducer.sum(), geometry: West_Provs.geometry(), scale: 30, maxPixels: 1e10});
                print('WEST PROVINCES LOSS: ', loss_W_prov.get('loss'), 'square meters');
                // Community Forest
                var loss_W_CF = areaLOSSImage.reduceRegion({
                        reducer: ee.Reducer.sum(), geometry: West_CF.geometry(), scale: 30, maxPixels: 1e10});
                print('WEST CF LOSS: ', loss_W_CF.get('loss'), 'square meters');

// Gain.
        // East
                // Provinces
                var gain_E_prov = areaGAINImage.reduceRegion({
                        reducer: ee.Reducer.sum(), geometry: East_Provs.geometry(), scale: 30, maxPixels: 1e10});
                print('EAST PROVINCES GAIN: ', gain_E_prov.get('gain'), 'square meters');
                // Community Forest
                var gain_E_CF = areaGAINImage.reduceRegion({
                        reducer: ee.Reducer.sum(), geometry: East_CF.geometry(), scale: 30, maxPixels: 1e10});
                print('EAST CF GAIN: ', gain_E_CF.get('gain'), 'square meters');
        // West
                // Provinces
                var gain_W_prov = areaGAINImage.reduceRegion({
                        reducer: ee.Reducer.sum(), geometry: West_Provs.geometry(), scale: 30, maxPixels: 1e10});
                print('WEST PROVINCES GAIN: ', gain_W_prov.get('gain'), 'square meters');
                // Community Forest
```

```
var gain_W_CF = areaGAINImage.reduceRegion({
        reducer: ee.Reducer.sum(), geometry: West_CF.geometry(), scale: 30, maxPixels: 1e10});
print('WEST CF GAIN: ', gain_W_CF.get('gain'), 'square meters');

// Area.
    // East
        // Provinces
            var EProv_area = East_Provs.geometry().area();
            var EProv_areaSqM = ee.Number(EProv_area);
            print('East Provinces AREA:', EProv_areaSqM, 'square meters');
        // Community Forest
            var ECF_area = East_CF.geometry().area();
            var ECF_areaSqM = ee.Number(ECF_area);
            print('East CF AREA:', ECF_areaSqM, 'square meters');
    // West
            var WProv_area = West_Provs.geometry().area();
            var WProv_areaSqM = ee.Number(WProv_area);
            print('West Provinces AREA:', WProv_areaSqM, 'square meters');
        // Community Forest
            var WCF_area = West_CF.geometry().area();
            var WCF_areaSqM = ee.Number(WCF_area);
            print('West CF AREA:', WCF_areaSqM, 'square meters');
```

A.6 Compare Control and Treatment in R: Difference-in-Difference model

```
# read in the deforestation and CF properties datasets, make them dfs
lossyear <- read_csv("cf_lossyear.csv")
properties <- read_csv("CF_table_new.csv")
as.data.frame(lossyear)
as.data.frame(properties)

# merge the dfs together, and choose relevant columns
cf_table <- merge(lossyear, properties, by = 'id', all = TRUE) %>%
  dplyr::select(id, lossyear, yr_approved, year)

# we want to know when the year of loss is greater than the year the CF was approved to just get the rows with the loss after the CF was established
cf_table$is_approved =
   ifelse(cf_table$year >= cf_table$yr_approved, 1, 0)

# set the NAs (non designated CFs) to 0
cf_table$is_approved[is.na(cf_table$is_approved)] <- 0

# model outcome (rate of deforestation) dependent on if CF is approved or not
model <- lm(cf_table$lossyear ~ cf_table$is_approved + as.factor(cf_table$id) + as.factor(cf_table$year))
summary(model)

# difference in difference which used a factor of dependent variable*time
cf_table$did = cf_table$year * cf_table$is_approved

didreg = lm(formula = lossyear ~ is_approved + year + did, data = cf_table)
summary(didreg)

# a different way of doing difference in different to check the results
didreg1 = lm(lossyear ~ is_approved*year, data = cf_table)
summary(didreg1)

# Repeat using percent loss instead of total loss
```

```
# reestablish data table with proportional loss
cf_table_new <- merge(lossyear, properties, by = 'id', all = TRUE) %>%
  dplyr::select(id, lossyear, yr_approved, year, Area) %>%
  mutate(area = Area*10000) %>% # hectares to m^2
  mutate(cf_perc_loss = lossyear/area) %>% # make it proportion of area
  dplyr::select(id, yr_approved, year, cf_perc_loss) %>%
  dplyr::filter(!(id %in% c(14,15,16,78,79)))
# 78 and 79 were blank, 14, 15, 16 were all Bisemulu, which is separated into 3 separate chunks so we weren't able to parse the deforestation and area for each chunk

# we want to know when the year of loss is greater than the year the CF was approved to just get the rows with the loss after the CF was established
cf_table_new$is_approved =
   ifelse(cf_table_new$year >= cf_table_new$yr_approved, 1, 0)

# set the NAs (non designated CFs) to 0
cf_table_new$is_approved[is.na(cf_table_new$is_approved)] <- 0

# a model displaying the importance of each factor
prop_model <- lm(cf_perc_loss ~ is_approved + as.factor(id) + as.factor(year), data = cf_table_new)
summary(prop_model)

# model using difference in difference in two different ways
cf_table_new$did = cf_table_new$year*cf_table_new$is_approved

didregnew = lm(formula = cf_perc_loss ~ is_approved + year + did, data = cf_table_new)
summary(didregnew)

didregnew1 = lm(formula = cf_perc_loss ~ is_approved*year, data = cf_table_new)
summary(didregnew1)

# calculate confidence intervals
confint(didregnew1)
```

Appendix B: Connectivity Analysis

B.1 Resistance Raster

Set Model Properties

For all the models below, model properties were set using the following environments to ensure that output files had the same extent, projects and cell size.

1) Under Model Properties -> ‘Environments’ check boxes for ‘Workspace’, ‘Processing Extent’, ‘Raster Analysis”, and “Output Coordinates”
2) Select ‘Value’
   - Set ‘Workspace’
     i) Assign Output and Scratch workspace geodatabases
   - Set ‘Output Coordinates”
     i) Output Coordinate System = ‘as specified below’
        (1) WGS_1984_UTM_Zone_35S
   - Set ‘Processing Extent’‘
     i) ‘Extent’ = ‘same as variable Extent’
   - Set ‘Raster Analyst’

i) ‘Cell Size’ = ‘As Specified Below’

(1) 30

Land Cover Resistance Model

Table B.1.i. **Land cover classifications.** Classifications of land cover selected based on importance to Grauer’s gorilla according to expert opinion from Dominique Bikaba at Strong Roots Congo.

Land Cover	Rank
Primary Forest	1
Secondary Forest	2
Forest-Savanna Mosaic	3
Savanna Woodland/Tree Savanna	4
Cultivated Areas	5
Shrubland	6
Wetlands	7
Grassland	8
Artificial Surfaces	9
Water Bodies	10

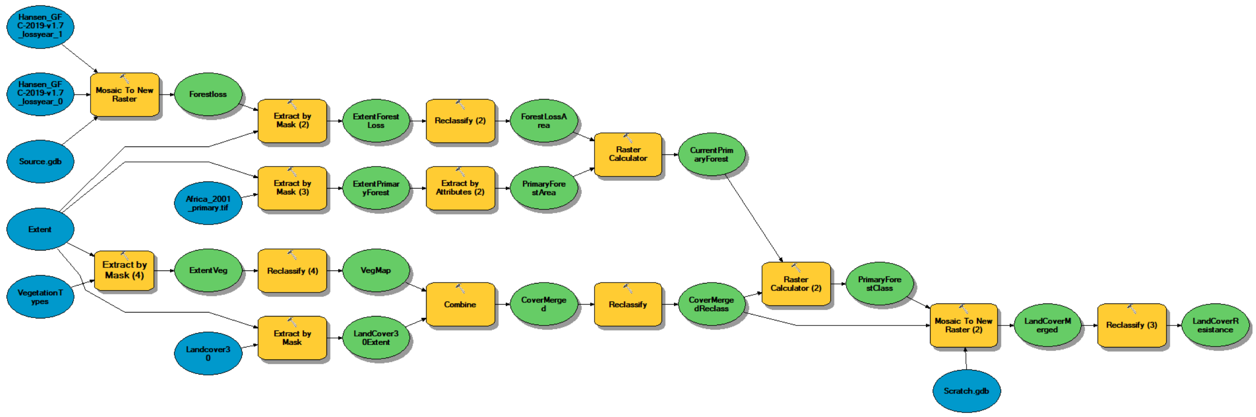

Figure B.1.i. Land Cover data. The model developed to create the land cover resistance layer is shown above. The tools used and their functions include:

- Mosaic to New Raster: Combine Hansen forest loss tiles into new combined forest loss raster
- Extract by Mask: Extract Forest Loss raster and Africa_2001_Primary raster by Extent raster
    - Extract by Attribute: Select only values greater than zero from 2001 Primary Forest raster to remove non primary forest areas
    - Reclassify: Assign values 1-19 as 1 and 0 as NoData to create binary forest loss layer
    - Raster Calculator: Remove areas of forest loss layer from Primary Forest raster using Con(IsNull("%ForestLossArea%"),"%PrimaryForestArea2001%")
- Extract by Mask: Extract ESA 2010/UCLouvain vegetation cover layer by Extent Raster
    - Reclassify: Reassign cell value for each vegetation type as a numeric value ranging from 1 to 10 based on habitat suitability for grauer's gorillas
- Extract by Mask: Extract GlobeCover30m land cover layer by Extent Raster
- Combine: Merge vegetation cover and land cover layer and assign a new value to each unique combination of input values
- Reclassify: Reassign each cell value in the combined raster as a numeric value ranging from 2 to 9 based on land cover classification (Table B.1.i.) based on the value of the 30m resolution land cover layer
- Raster Calculator: Create primary forest land cover class layer using Con(("%CoverMergedReclass%" == 2)|("%CurrentPrimaryForest%" == 1), 1)
- Mosaic to New Raster: Add primary forest land cover class layer with cell value 1 to the combined land cover layer (Mosaic operator: First, keeping primary forest land cover class layer cell values)
- Reclassify: Convert land cover classification ranks to resistance values (Table 1)

Elevation Resistance Model

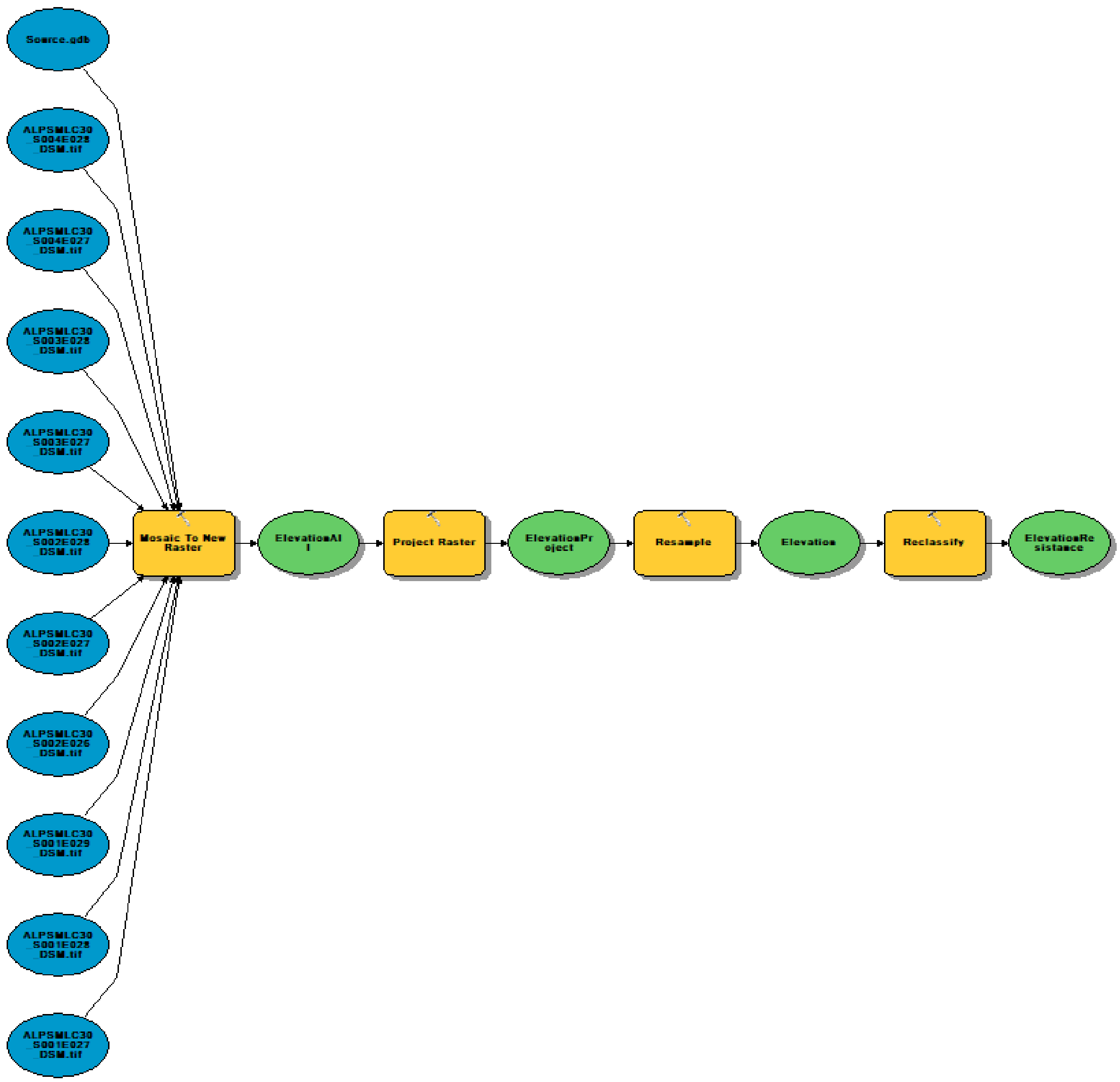

Figure B.1.ii. Elevation & slope rasters. DSM data was acquired from Japan Aerospace Exploration Agency, compiled, and classified based on the upper elevation limit of grauer gorillas.

- Mosaic to New Raster: Combined tile DSM rasters into a single raster
- Project Raster: Project Raster into coordinate system WGS_1984_UTM_Zone_35S
- Resample: Resample elevation layer to cell size 30m
- Reclassify: Assign values <2500m above sea level as 1 and values >2500m above sea level as 2

Human Footprint Resistance Model

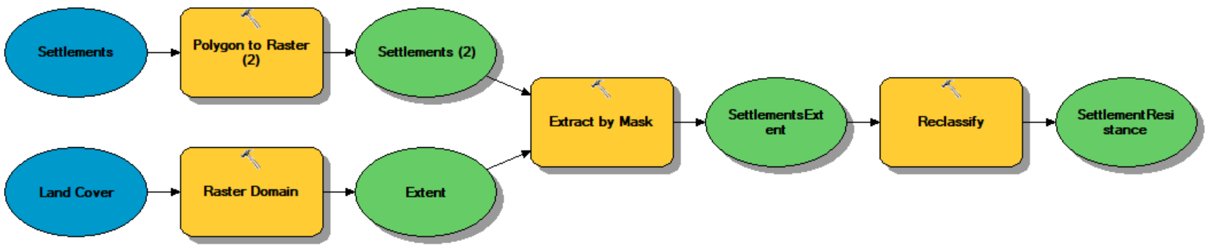

Figure B.1.iii. Human footprint data. The model developed to create the settlements resistance layer is shown above. The tools used and their functions include:

- Polygon to Raster: Convert settlement polygons to raster layer
- Raster Domain: create polygon based on outline of land cover layer to use as exent mask
- Extract by Mask: Extract Settlements layer by Extent raster
- Reclassify: Reassign values for built up areas and small settlement areas to 1000 and hamlets to 100

Roads Resistance Model

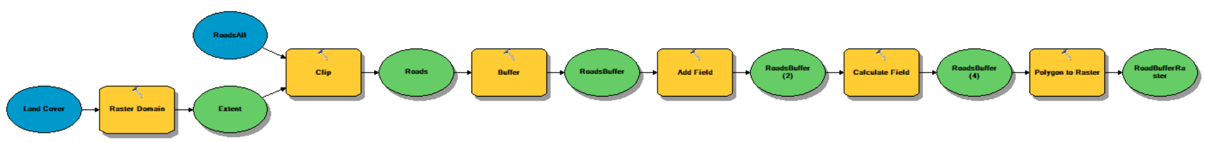

Figure B.1.iv. Roads data. The model developed to create the roads resistance layer is shown above. The tools used and their functions include:

- Raster Domain: create polygon based on outline of land cover layer to use as exent mask
- Clip: clip roads to layer to extent
- Buffer: Apply 5m buffer to either side of roads
- Add Field: Add field for cell value to attribute table
- Calculate field: Assign value field with cell value of 25
- Polygon to Raster: Convert layer to raster

Combined Resistance Model

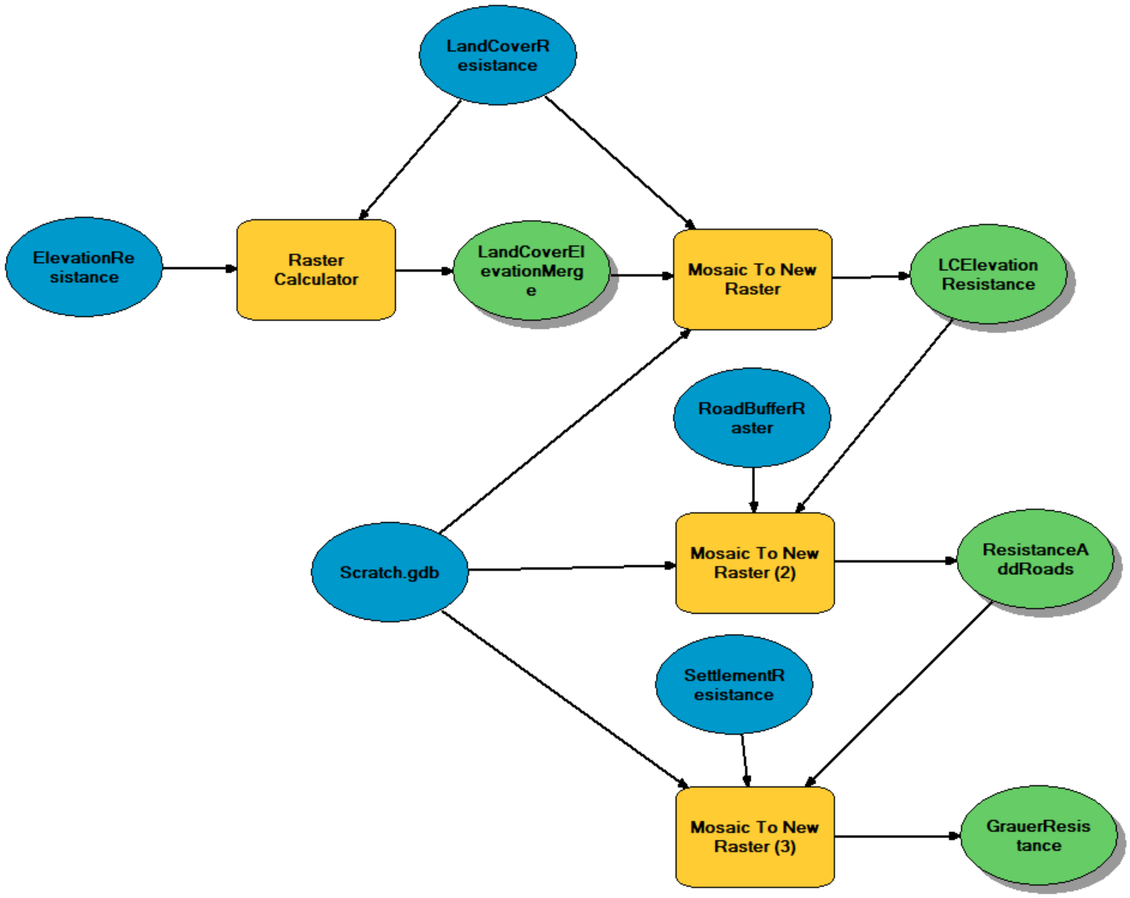

Figure B.1.v. Combined resistance data. The model developed to create the final combined resistance layer by iteratively combining the individual feature resistance layers is shown above. The tools used and their functions include:

- Raster Calculator: Combine Elevation Resistance with Land Cover Resistance to create new layer with increased resistance for all land cover classes when above 2500m.a.s.l using
  Con(("%LandCoverResistance%" == 1) & ("%ElevationResistance%" == 2), 70,
  Con(("%LandCoverResistance%" == 10) & ("%ElevationResistance%" == 2), 75,
  Con(("%LandCoverResistance%" == 40) & ("%ElevationResistance%" == 2), 80,
  Con(("%LandCoverResistance%" == 50) & ("%ElevationResistance%" == 2), 80,
  Con(("%LandCoverResistance%" == 65) & ("%ElevationResistance%" == 2), 80)))))
- Mosaic to New Raster: Combine land cover resistance layer below 2500m.a.s.l with land cover resistance layer above 2500m.a.s.l (Mosaic Operator: First, keeping land cover resistance >2500m.a.s.l cell values)
- Mosaic to New Raster: Combine land cover/elevation resistance layer with roads resistance layer (Mosaic Operator: Maximum)
- Mosaic to New Raster: Combine Land Cover/Elevation/Roads resistance layer with settlements resistance layer (Mosaic Operator: Maximum)

Final Resistance Layer

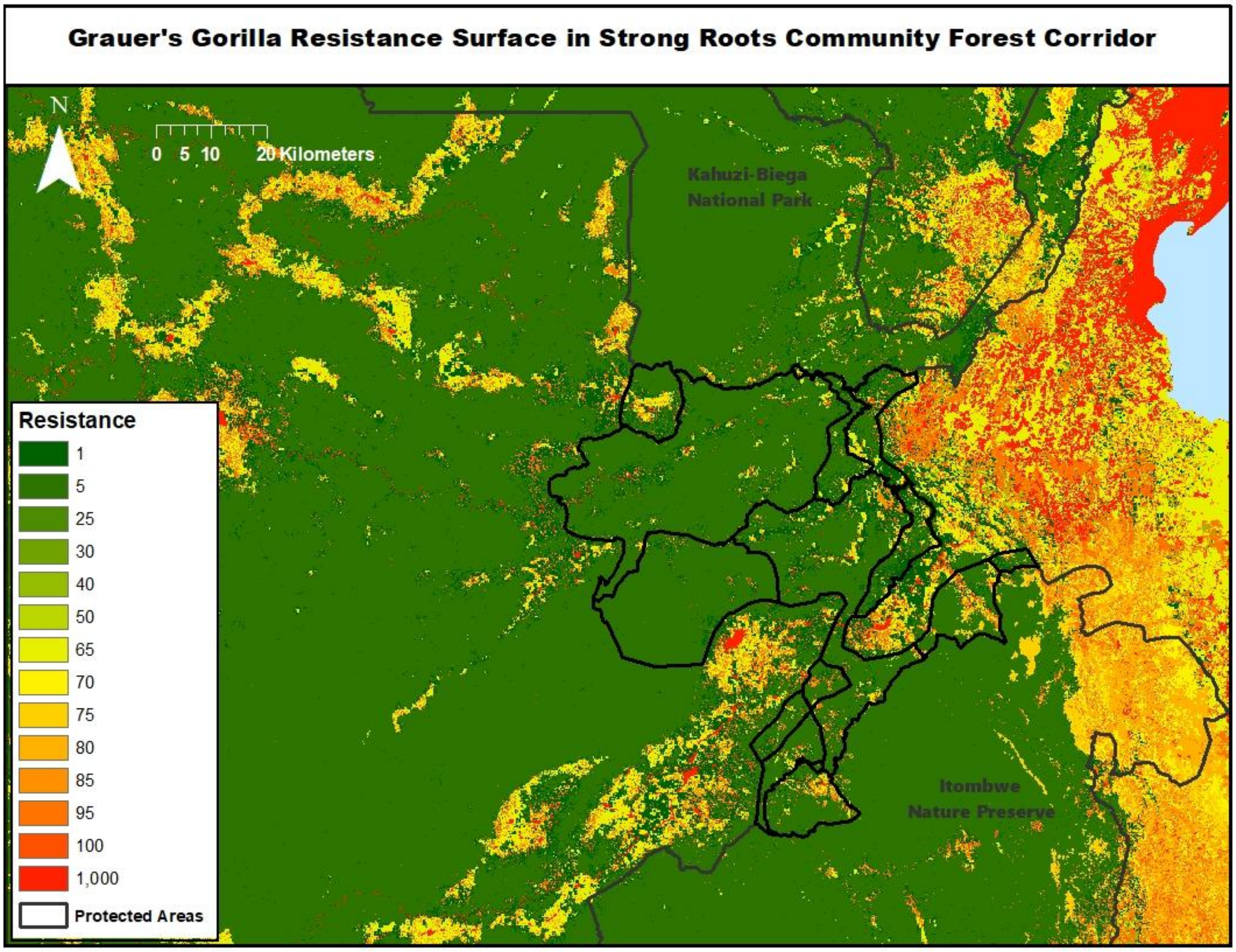

Figure B.1.vi. Final Resistance Layer. The final resistance layer used in the connectivity analysis model, where 1 represents areas of no resistance to movement shown in dark green and 100 indicates the highest resistance where movement is still possible in dark orange. A resistance value of 1,000 was assigned to landscape features that represent an absolute barrier to movement, such as water bodies and large settlements, shown in bright red.

B.2 Connectivity, Pinch Point & Barrier Model

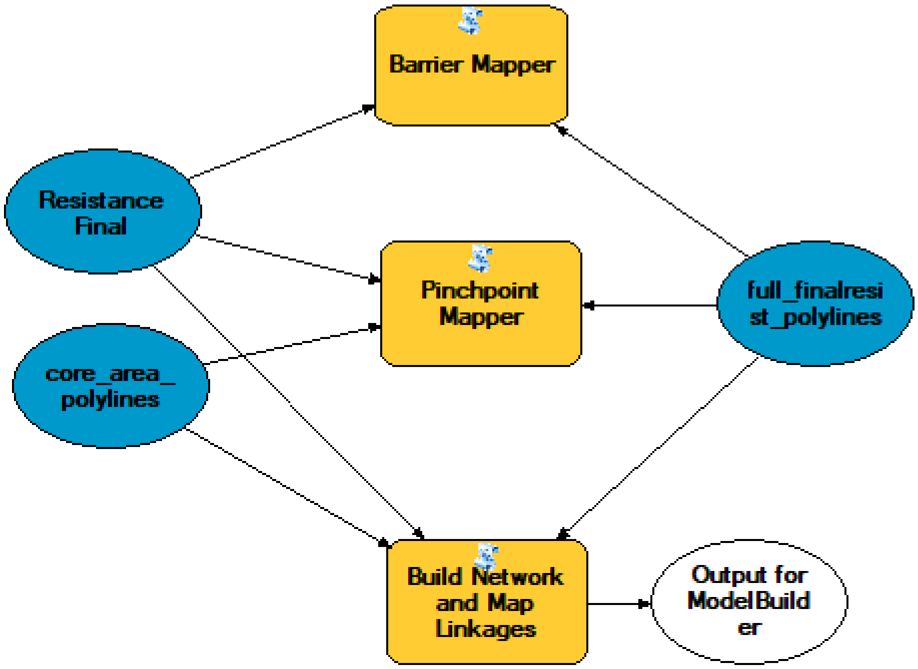

Figure B.2.i. Combined connectivity analysis. The model developed to create maps of corridor connectivity, the least-cost path, pinch points and barriers. The tools used and their functions include:

- Build Network and Map Linkages: Core Area Feature Class was set to 'core_area_polylines' and the Resistance Raster to 'Resistance Final'. Process Steps selected in Linkage Mapper were 1, 2 (Cost Weighted & Euclidean), 3 (Drop Corridors That Intersect Core Areas checked) and 5 (Cost-Weighted Distance Threshold to Use in Truncating Corridors set to 100,000 m)
- Pinch Point Mapper: Core Area Feature Class was set to 'core_area_polylines' and the Resistance Raster to 'Resistance Final'. CWD Cutoff Distance was set to 50,000 m and Calculate Adjacent Pair Pinch Points Using Circuitscape (optional) was selected.
- Barrier Mapper: Core Area Feature Class was set to 'core_area_polylines', and the Resistance Raster to 'Resistance Final'. The Minimum Detection Radius was set to 40 m and the Maximum Detection Radius was set to 400 m, with the Radius Step Value set to 40 m

Appendix C: Community Wellbeing & Opinions

C.1 Determination of distance to protected area

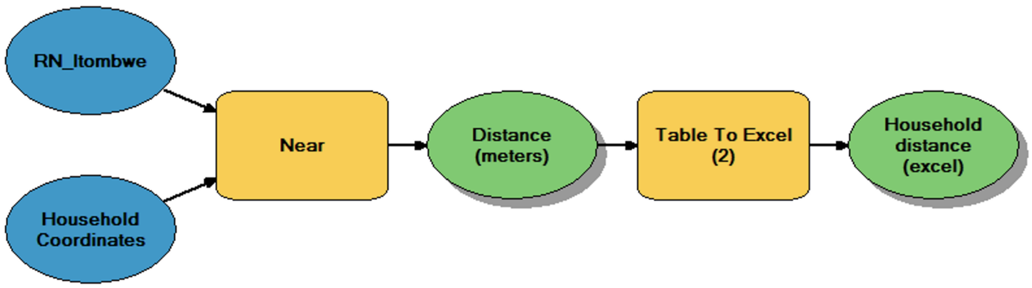

Figure C.1.i. ArcGIS Model Builder model used to determine each respondent's distance to Itombwe Nature Reserve. The model provided the distance of a respondent in meters to Itombwe Nature Reserve.

C.2 Determination of distance to pinch point

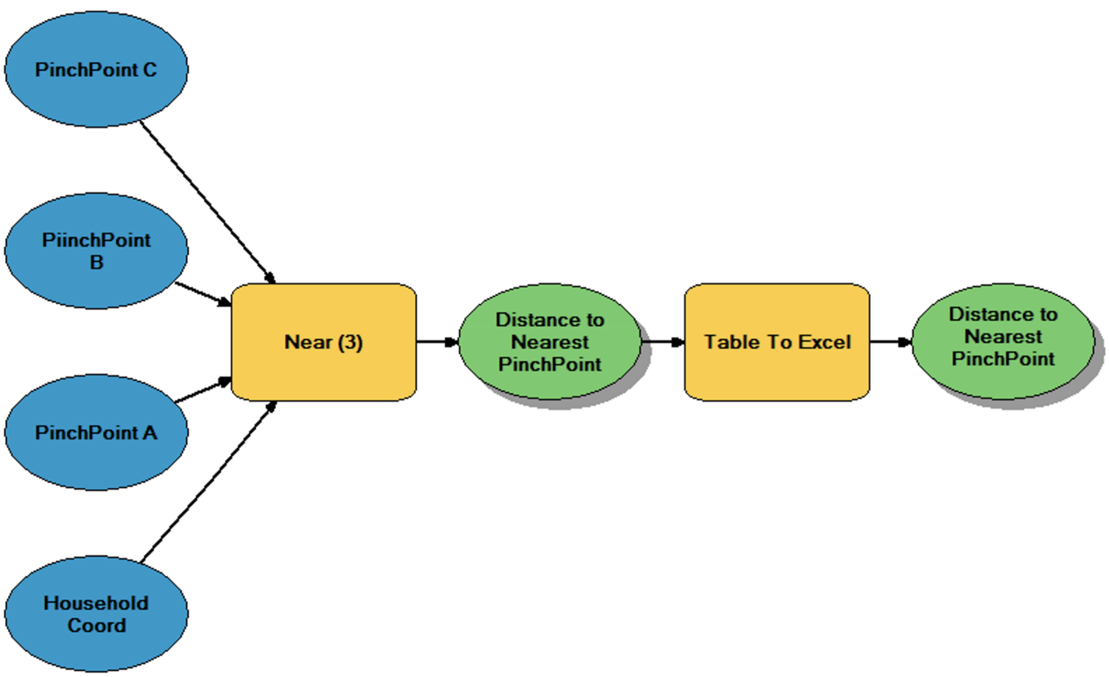

Figure C.2.i. ArcGIS Model Builder model used to determine the each respondent's distance to the nearest pinch point determined in connectivity analysis

- The search radius of the Near tool was limited to 10,000 meters
- Each respondent was categorized into which pinch point they were most near with the associated distance

---

Appendix D: Future Climate Scenarios

D.1 Variable Processing for Maxent

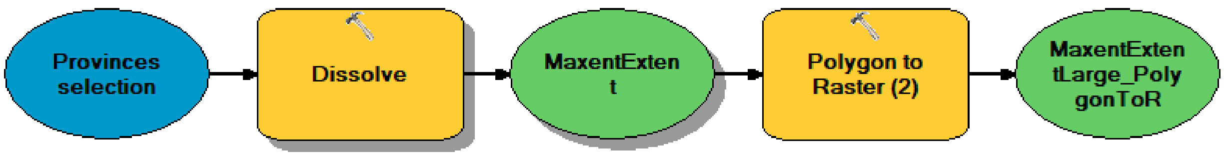

Figure D.1.i. Maxent Extent. The model developed to create the extent used for all Maxent variable processing is shown above. The tools used and their functions include:

- Dissolve: Remove borders between Sud-Kivu, Nord-Kivu and Maniema provinces to create single combined polygon shape
- Polygon to Raster: Convert extent polygon to raster layer to be used as mask for all Maxent variable models

Set Model Properties

For all the models below, model properties were set using the following environments to ensure that output files had the same extent, projects and cell size.

1) Under Model Properties -> 'Environments' check boxes for 'Processing Extent', 'Raster Analysis", and "Output Coordinates"
2) Select 'Value'
    - Set 'Output Coordinates"
        - i) Output Coordinate System = 'as specified below'
            - (1) WGS_1984_UTM_Zone_35S
    - Set 'Processing Extent''
        - i) 'Extent' = 'as specified below'
        - ii) 'Snap Raster' = 'same as MaxentExtent"
    - Set 'Raster Analyst'
        - i) 'Cell Size' = 'same as cbio1'

Climate Variables Model

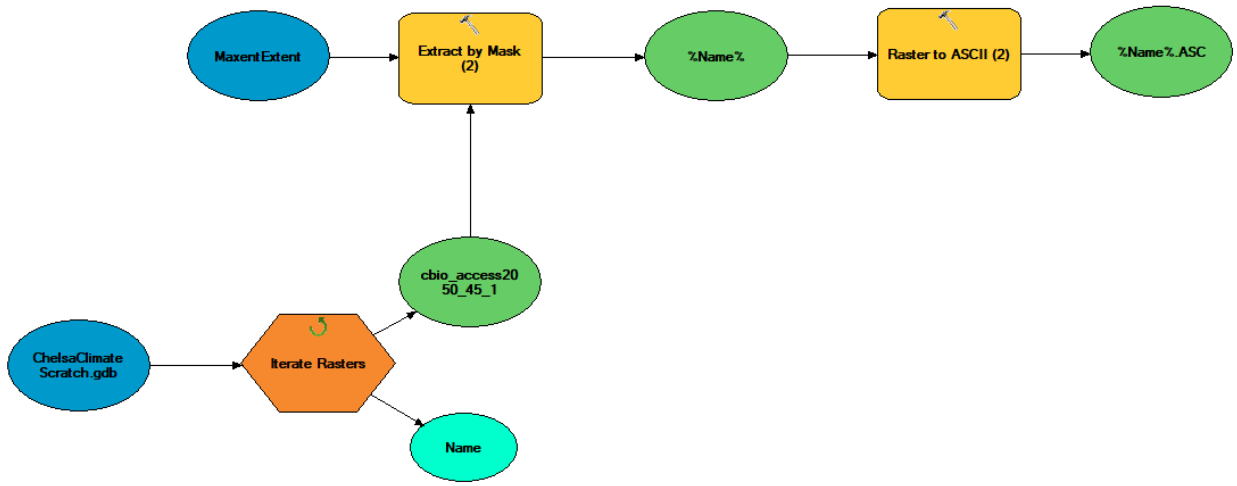

Figure D.1.ii. Chelsa climate variable data. The model developed to create bioclimatic variable ASCII files for all climate scenarios is shown above. The tools used and their functions include:

- Iterate Rasters: the iterate tools ensured that all climate rasters were processed through the model. Wildcard was set to 'cbio*' and the box for 'recursive' was checked.
- Extract by Mask: Extract the current raster iteration using the layer Maxent Extent
- Raster to ASCII: Convert current raster iteration to ASCII file and save it to the Maxent Inputs folder

Categorical Variables Model

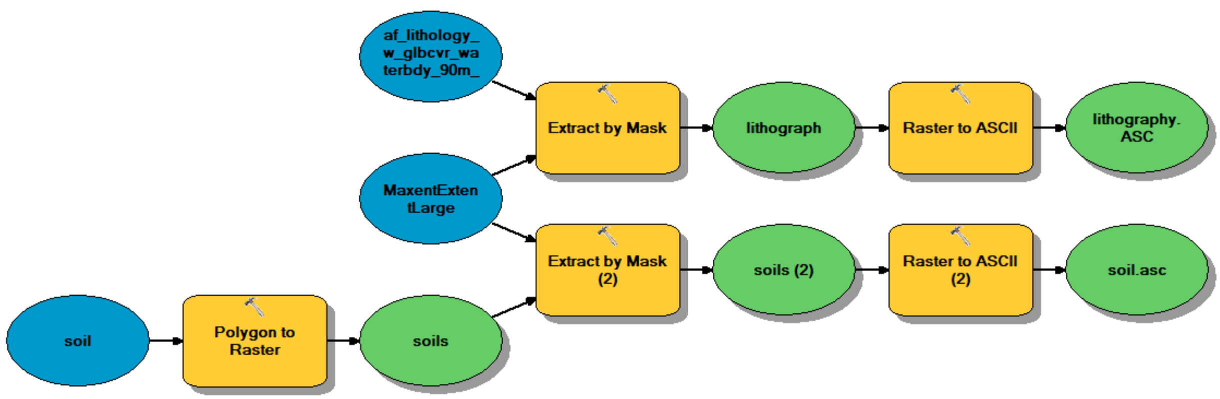

Figure D.1. iii. Soils and lithography variables data. The model developed to create soil and lithography variable ASCII files is shown above. The tools used and their functions include:

- Polygon to Raster: Convert soils data to raster format
- Extract by Mask: Extract Soils and Africa Lithography layers by Maxent Extent layer
- Raster to ASCII: Convert soils and lithography rasters to ASCII files and save it to the Maxent Inputs folder

D.2 Maxent Model Input Parameters

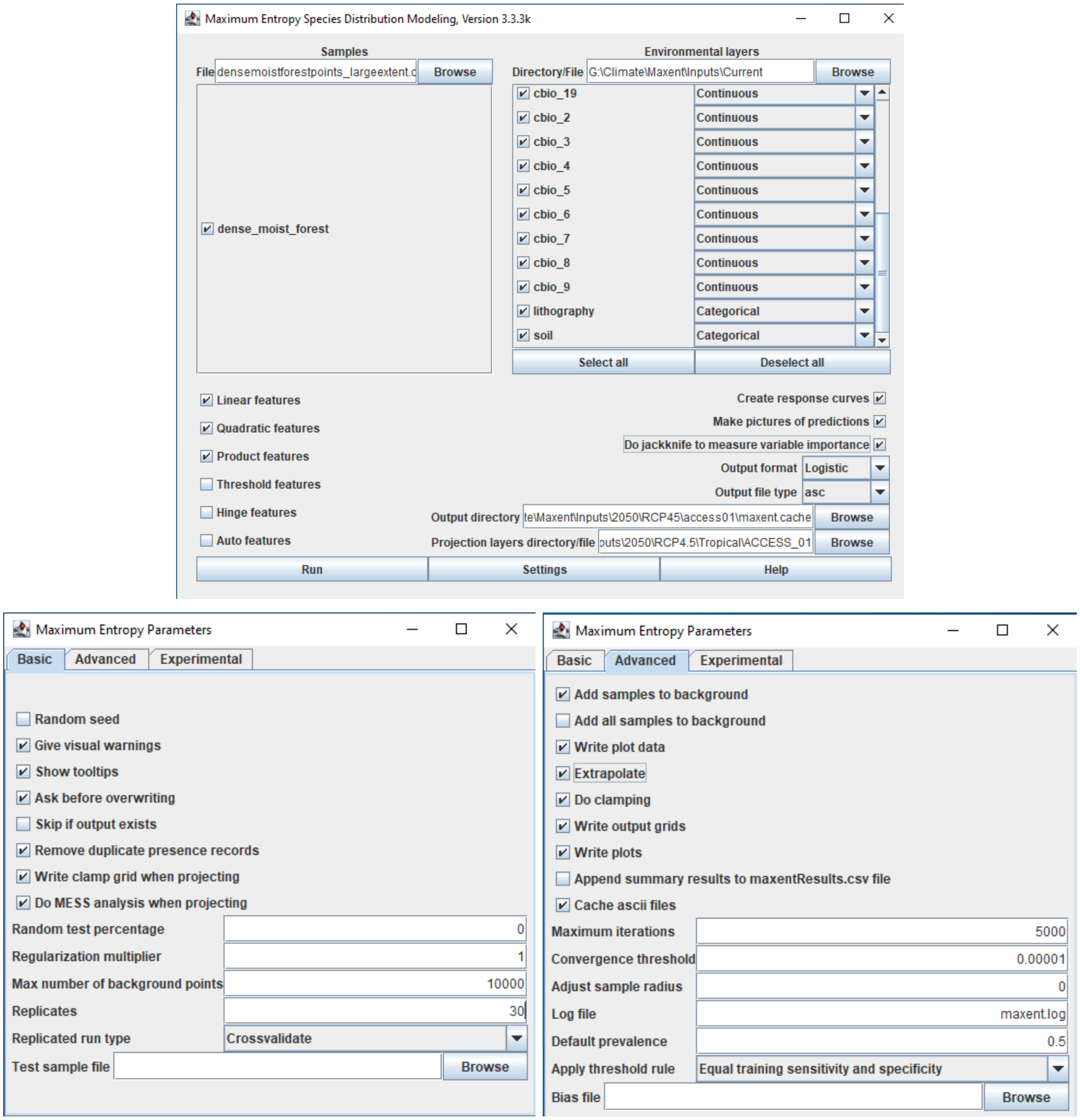

Figure D2.i. Maxent parameter settings used for all runs. Top: File input settings. Bottom: Basic and advanced parameter settings.

D.3 Habitat Suitability

Table D.3.i. Maxent AUC values and calculated suitability threshold values for binary forest type presence/absence predictions averaged across 30 replicates

Forest Type	Area Under the Curve	Equal Training Sensitivity and Specificity Threshold
Dense Moist Tropical Forest	.701	0.478
Submontane Forest	.911	0.4305
Montante Forest	.926	0.4057

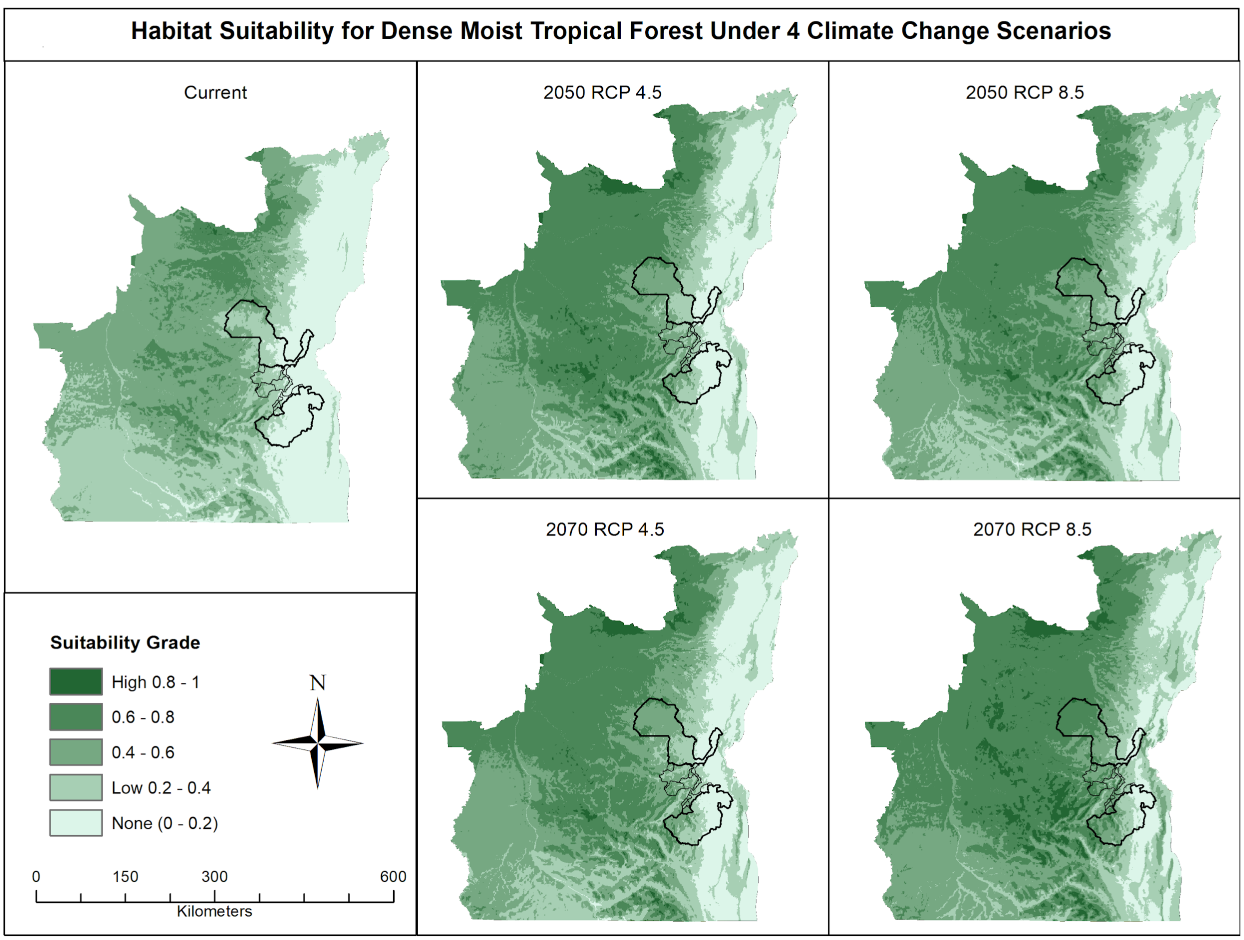

Figure D.3.ii. The probabilistic distribution of current suitable conditions for dense moist tropical forest in the Sud-Kivu, Nord-Kivu and Maniema provinces, Democratic Republic of Congo during the present day, 2050s and 2070s under different climate scenarios. The map shows the average probabilistic distribution for 5 GCM's across 30 Maxent replicates (AUC = .701). Green indicates high probability of suitable conditions, yellow indicates conditions typical of those where the species is found, and blue indicates low predicted probability of suitable conditions.

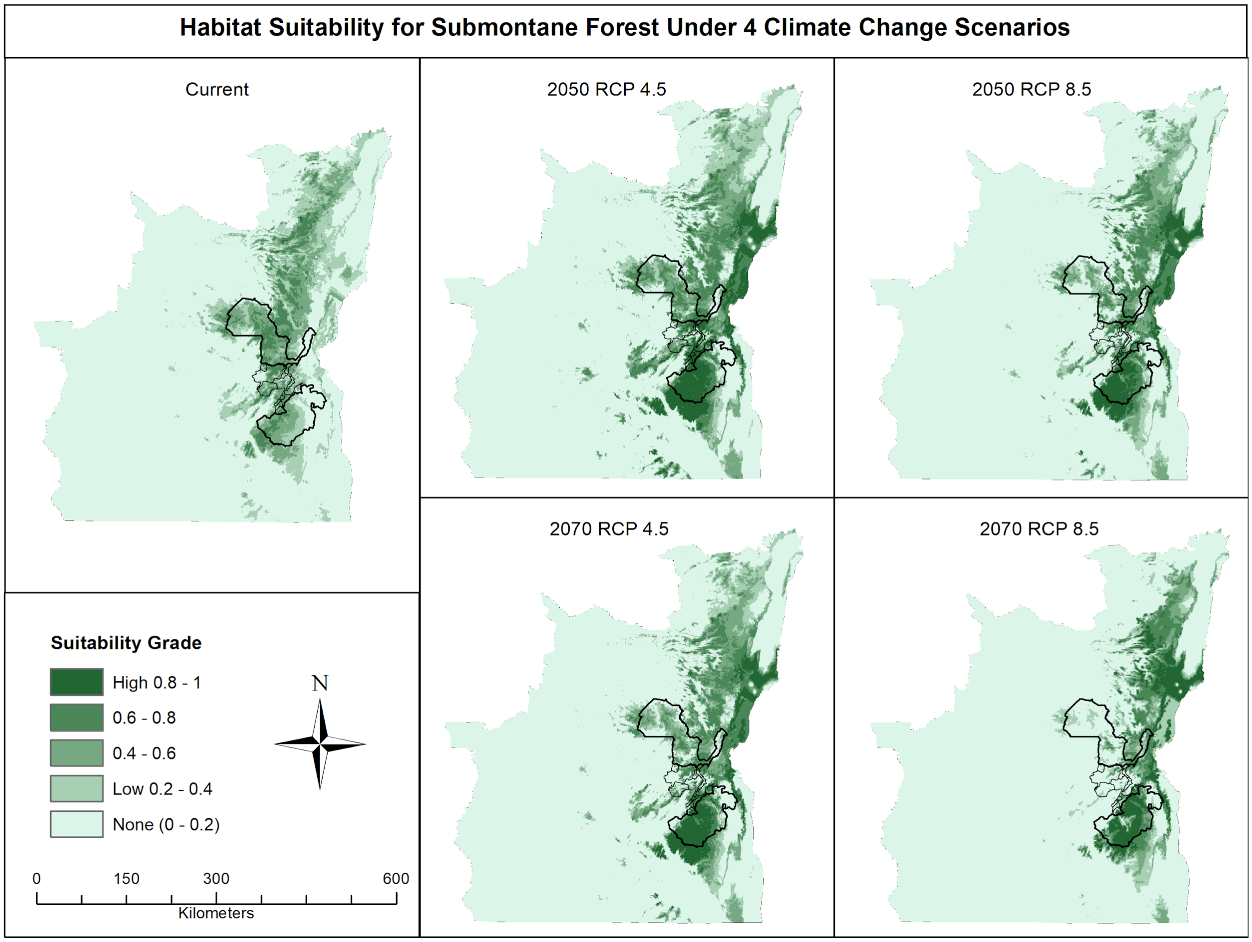

Figure D.3.iii. The probabilistic distribution of current suitable conditions for submontane forest in the Sud-Kivu, Nord-Kivu and Maniema provinces, Democratic Republic of Congo during the present day, 2050s and 2070s under different climate scenarios. The map shows the average probabilistic distribution for 5 GCM's across 30 Maxent replicates (AUC = .911). Green indicates high probability of suitable conditions, yellow indicates conditions typical of those where the species is found, and blue indicates low predicted probability of suitable conditions.

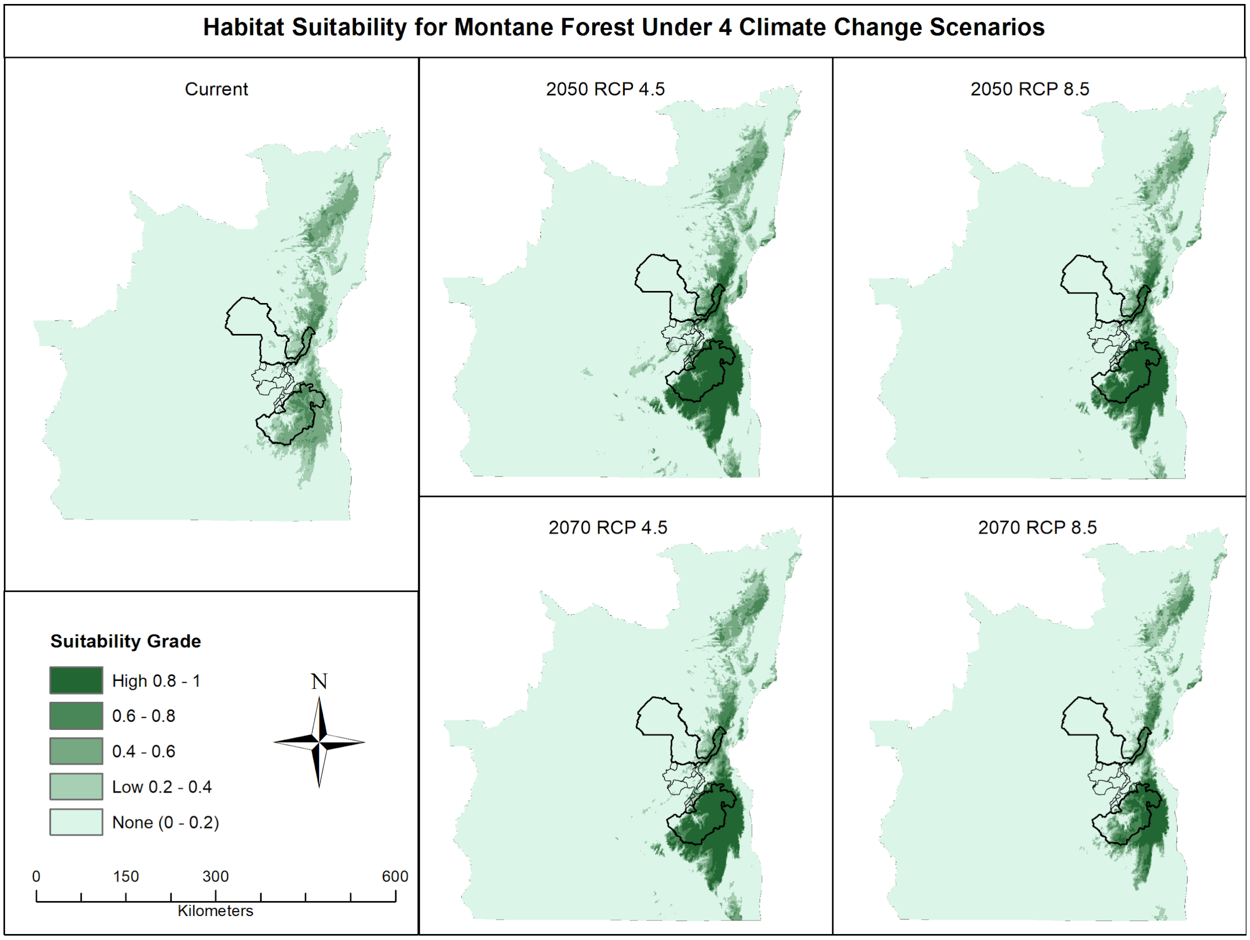

Figure D.3.iv. The probabilistic distribution of current suitable conditions for montane forest in the Sud-Kivu, Nord-Kivu and Maniema provinces, Democratic Republic of Congo during the present day, 2050s and 2070s under different climate scenarios. The map shows the average probabilistic distribution for 5 GCM's across 30 Maxent replicates (AUC = .926). Green indicates high probability of suitable conditions, yellow indicates conditions typical of those where the species is found, and blue indicates low predicted probability of suitable conditions.