Spatial modelling of mountain gorilla (*Gorilla beringei beringei*) habitat suitability and human impact

Virunga Volcanoes Mountains, Rwanda, Uganda and Democratic Republic of Congo

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February, 2008

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By

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Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialisation: (Natural Resource Management: Environmental System Analysis and Management)

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Abstract

The aim of this study is to model the actual/potential biophysical habitat suitability of mountain gorillas (*Gorilla beringei beringei*) with and without the current human impact. The research area is in the Virunga Volcanoes Mountains shared by Rwanda, Uganda and Democratic Republic of Congo in East-Central Africa. The findings of the modelling are to be used for spatially-specific recommendation on optimizing mountain gorilla conservation management. Two habitat modelling algorithms (MAXENT and GARP) have been applied on mountain gorilla presence-only data and a set of plausible habitat variables. MAXENT (AUC = 0.89) performed better over GARP (AUC = 0.80) using the variables: elevation, slope steepness, incoming solar radiation and vegetation types. A vulnerability of mountain gorillas for human impact map was generated based on travelling time (distance, slope, roads, and cover) from the villages. Gorilla habitat suitability has been overlaid with the vulnerability map and the actual human impact. A negative correlation is found between gorilla locations and human impact locations implying that mountain gorillas avoid human impact. Association between vulnerability areas and suitability areas is also found with important spatial overlap of suitable habitat (26%) falling into vulnerable to high vulnerable areas and are affected by 86% of human impact. These results emphasize the need for better conservation practices.

Keywords: habitat modelling, habitat suitability, MaxEnt, GARP, Virunga Volcanoes, Gorilla, human impact, presence-only, great apes, Rwanda, Uganda, Congo

Acknowledgements

I would like to express my sincere gratitude to people who helped me in some ways or other during this research process. My sincere thanks are addressed:

First and foremost to my first supervisor, Dr Hein van Gils, for his guidance, good comments and rich discussions all along the thesis. My thanks go also to my second supervisor, Drs Eduard Westinga, for his advice especially on image classification;

To the Office Rwandaise du Tourisme et des Parcs Nationaux (ORTPN) for permission to work in the park and for providing the data to me;

To the Dian Fossey Gorilla Fund International / Karisoke Research Center for the immense support during my field work. My sincere gratitude goes to Dr Katie Fawcett, Director of Karisoke Research Center, and to the dedicated team of researchers, trackers and rangers who contribute to the mountain gorilla conservation and to the data collection;

To the field work team Aimable Nsanzurwimo (KRC botany research coordinator), Jean Bosco Bizumuremyi (field operations coordinator), Joseph Mpazayabo (tracker), Nzeyimana (local defence), Alphonse Hakizimpfura (driver), the students from the National University of Rwanda, Olivier and Leonard, and to the military escort;

To the Netherlands Government through NUFFIC funding (NPT/RWA/071) and ITC for providing me with the opportunity to pursue my Master's studies;

To the National University of Rwanda (NUR) and the Centre for Geographic Information Systems and Remote Sensing of NUR for study leave permission and all other support during my studies;

To my friends and classmates with whom we shared the good and hard moments of school life;

Last but not least, to my parents, brothers and sisters and to my fiancée Immaculée Edith Giraso for their remote encouragement.

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1. Introduction

1.1. Background

1.1.1. Habitat destruction

The term Habitat has been recognized as a key concept in ecology and wildlife management and distribution (Corsi et al., 2000; Southwood, 1977). It is defined as the locality in which a plant or animal naturally grows or lives no matter how briefly and/or as the actual or potential environment where a species lives (de Leeuw et al., 2006; Liu et al., 2005b). More definitions of the term habitat are found in Corsi et al.(2000) where a classification of various definitions of habitat is made according to whether it relates to biota (species and or communities) or to land or whether it relates to Cartesian (geographic location) or to environmental space (environmental envelopes) or both. For all these definitions, the term habitat is regarded as a property of a specific species (de Leeuw et al., 2002). The changes in habitat definitions evolved initially from the species-related concept (description of the environment in which a species lives) to land-related concept (description of occurrence of species in "habitat" (land unit) types) (Corsi et al., 2000). The latter arose with the development habitat mapping where the term habitat refers to homogeneous land units or suitable land for wildlife (habitat suitability index models or habitat suitability map) and where these maps refer to unit of land rather than specific species (Corsi et al., 2000; de Leeuw et al., 2002) leading to ambiguity in the use of the term habitat i.e. all land should be considered as habitat whether suitable or not otherwise unsuitable habitat should be non habitat. To avoid this contradiction of the term of habitat, in this study, the term habitat is used in reference to specific wildlife species (e.g. Mountain gorilla habitat suitability).

Habitat destruction is a main factor at the origin a species population to decline, eventually leading to it being endangered, or even to its extinction. Habitat destruction takes several forms: complete loss of areas used by species; degradation, for example, from vegetation removal and erosion; and fragmentation, when species are constricted onto small patches of undisturbed land surrounded by areas cleared for agriculture and other purposes (Vanreusel and Van Dyck, 2007).

The changes in habitat can be natural or human related. Natural changes (volcanic eruptions, floods…) tend to occur at a slow speed, usually causing only a slight impact on individual species while human related changes normally occur at a fast speed, giving little or for individual species to react and adjust to new circumstances (Pimm, 2006). For this reason, rapid habitat loss is the primary cause of species endangerment and can lead to catastrophic

results. Human related activities are the strongest forces in rapid habitat loss as the result of land use changes. Nearly every region of the earth has been affected by human activity (Lewis, 2006; Pimm, 2006).

Habitat Loss, degradation and fragmentation are the most crucial process contributing to global biodiversity losses and are among the greatest challenges that face the world (Sanchez-Hernandez et al., 2007). Since the United Nations Summit conference at Rio de Janeiro in 1992 that resulted in agreement by world government leaders on a Biodiversity Convention for species and habitat protection and an agenda for sustainable development (Agenda 21) (United Nations, 1994). Many countries have signed and rectified the Convention on Biological Diversity (CBD) ensuring their commitment to protect the biodiversity as well as their environment.

This is the case for Uganda, Democratic Republic of Congo and Rwanda who signed the Convention on Biological Diversity and ratified it respectively in 1993, 1994 and 1995 to show their commitment to all issues concerning conservation and sustainable use of their resources (MINITERE, 2003; Republic of Uganda, 1998).The conservation of biodiversity has been the major concern since the colonial period, in these countries, with the establishment of protected areas. While in Congo protected areas cover 10 % in Uganda they cover 15% and in Rwanda 7.7 (Inogwabini et al., 2005; MINITERE, 2003; Republic of Uganda, 1998). These protected areas have not been spared from changes which resulted in the spatial reduction of their area due to many factors among others land use change especially for agriculture land, exploitation of forest resources and forest mismanagement (MINITERE, 2000; Republic of Uganda, 1998).

The increase of the population is followed by an increased population density that led to increased demand for natural resources (land, water, energy, food, etc.), land clearing for agriculture and grazing, house building, removal of plants for different purposes, etc. Population density being highly correlated with rainfall distribution, this emphasizes more the predominance of agriculture as major land use activity (Cordeiro et al., 2007). As a result, the protected areas were the first to face these consequences, for example, Rwanda has lost more than 60% of its protected areas during the period from 1960 – 2001 (MINITERE, 2003) and Uganda has lost 25% of its forests since 1890 (Republic of Uganda, 1998). The decline of protected areas has caused the loss of habitats which led to the loss of their fauna and flora where some animals and plants species became totally extinct, others very rare or extremely reduced (MINITERE, 2000).

1.1.2. Mountain gorilla conservation and habitat destruction

Two species of gorillas are distinguished: the western gorillas (*Gorilla gorilla*) and the eastern gorillas (*Gorilla beringei*). The western gorillas comprise of the cross river gorillas (*Gorilla*

gorilla diehli) and the western lowland gorilla (*Gorilla gorilla gorilla*) while the eastern gorillas include eastern lowland gorilla (*gorilla beringei gaueri*) and mountain gorilla (*Gorilla beringei beringei*). Mountain gorilla (*Gorilla beringei beringei*) are distributed in two populations one living in the Virunga Volcanoes Mountains between Rwanda, Democratic Republic of Congo and Uganda and estimated to 380 individuals (Gray et al., 2005) and another one in Bwindi Impenetrable National Park in Uganda with approximately 320 individuals (Werikhe et al., 1998). There is a taxonomic debate on the latter to be a different subspecies but no formal description has yet been published.

The genus gorilla is endangered and Mountain gorilla (*Gorilla beringei beringei*) is categorized as critically endangered species on the IUCN red list in 2000 (Butynski, 2000) and are covered by many international treaties among others the Convention on Migratory Species (CMS) and Convention on International Trade on Endangered Species (CITES). The conservation of mountain gorillas started in 1925 with the creation of Albert National Park by Albert I of Belgium (Akeley, 1931). In 1960, with the independence of Congo, the park was split into three parts: Parc National des Virunga (PNVi) in Congo, Parc National des Volcans (PNV) in Rwanda and Mgahinga Gorilla National Park (MGNP) in Uganda.

Mountain gorillas are at the end of the gorillas' distribution at an altitude ranging up to 4507 m in the Virunga Volcanoes Mountains where they are endemic (Stuart 1999). They are primarily herbivore and the majority of their diet is composed of the leaves, shoots and stems. they also feed on bark, root, flowers, and fruit (1.7%), as well as larvae, snails and ants (0.1%) (Fossey, 1977). Their home range size is influenced by availability of food sources and social factors and usually includes several vegetation belts including the bamboo forests at 2 225–2 804 m; the *Hagenia* forests at 2 804–3 353 m; and the giant S*enecio* belt at 3 444–4 267 m (Schaller, 1963). In addition the forage seems to provide sufficient moisture so that mountain gorillas rarely consume water.

Habitat loss, poaching, human disease and war are among the main risks that face mountain Gorillas. The Mountain gorillas are mainly threatened by habitat loss. The habitat loss has confined the mountain gorillas into remnants habitats in high altitude (Weber, 1983). This loss of habitat combined with the poaching of gorillas in the 1970s are at the origin of the dramatic decline of mountain gorilla population in the Virunga Volcanoes Mountains as well as the extinction and reduction of some other species (Weber, 1983; Weber, 1987). Today the population is recovering due probably to the conservation activities (Plumptre et al., 2007). However, any other change in the habitat could reverse this trend in the mountain gorilla population.

The increase of the human population density has reduced the size of the park considerably due to the increase need for land and forest resources. It is estimated that more than 37 percent of afromontane forests in Africa have been lost to agriculture or timber production (Adeleke,

1996). The region is among the most heavily populated parts of rural Africa. As an example, districts around the park on Rwandan side record around 500 inhabitants per square kilometre (MINECOFIN, 2004). The rich volcanic soil and high rainfall make the region very suitable for agriculture, consequently, putting an extreme pressure on the park (Weber, 1987). Since 1958, the park on the Rwandan side would have been reduced up to 54% (Weber, 1987) and on the Ugandan side in 1951 the park border was shifted from 2450m to 2740 m of altitude (Gray et al., 2005; Republic of Uganda, 1998).

People around the park are generally peasants and more than 90% depend mostly on the subsistence agriculture (MINECOFIN, 2004). The increase of the human population has reduced considerable land utilized per household limiting their production and increasing the poverty in the population. The majority of the human population in this region has been classified as living in extreme poverty, with more than 50% lacking sufficient land to meet their basic needs (Lanjouw et al., 2001). Having no other source of revenue, they turn to the resource of the park as source of food and income.

As a result, several form of human presence is registered in the park which poses direct and indirect threat to mountain gorillas. This is the case for illegal activities consisting mainly of poachers, wood/bamboo cutters, water collectors, honey collectors, etc. (Gray and Kalpers, 2005).

Direct poaching for mountain gorillas is less frequent as people around the Virunga Volcanoes Mountains traditionally do not consume gorillas' meat. However, poaching of gorillas for trophies and selling of infants in the zoos were more present in the 1970s. Even though this type of activity is reported to have been ceased in the early 1980s, in 2002, direct poaching of gorillas reappeared where at least 11 gorillas were killed (4 males, 6 females and 3 infants) in capturing infants for probably trading (Gray et al., 2005). Generally, poaching by snares of ungulates is more often observed and increases indirectly a threat to mountain gorillas as snares set for ungulates may cause serious and deadly injuries to mountain gorillas especially infants and juveniles. Furthermore, the threat to mountain gorillas can be increased by disease that can be transmitted by closely related species like humans (Kalema-Zikusoka et al., 2002). Transmission of these diseases can be possible when humans get into contact with mountain gorillas, which is the case for different human presence in the park whether legally (park staff, researchers, tourists) or illegally (e.g. poachers).

Several studies have been done in relation to mountain gorilla distribution and habitat. Most of those studies are focused on habitat use in relation to social behaviour of mountain gorilla (Watts, 1990; Watts, 1994; Watts, 1991); or to vegetation distribution, food quality and availability, seasonality and carrying capacity (McNeilage, 1995; Watts, 1991; Watts, 1998a; Watts, 1998c) to the presence of other mammals (Plumptre, 1996) or to hazard risk (Watts, 1991) and are based on expensive and time consuming methods. Few have integrated

available spatial geographic information (satellite images, GPS data, land use maps, DEM, etc.) into geographic information systems (GIS) and remote sensing to spatially model the habitat suitability in relation to environmental predictors and/or human activities what is the aim of this study.

1.1.3. Spatial modelling of habitat suitability

In order to determine potential conflicts between land uses and natural resources, it is necessary to know where those natural resources are located. Historically, mapping of resource locations has involved extensive field work over large areas even though the resource maybe located patchily within the area. Geographic information system (GIS) technology provides the ability to construct models of habitat that rely on existing or readily obtained information (e.g., remotely sensed images, soil surveys, digital elevation models, geological surveys, topographic maps, etc.).

Models predicting species and environment relationship have been the central concern in ecology (Guisan and Zimmermann, 2000) and have been used to wildlife management issues such as managing species distribution, assessing ecological factors of various species, risk of biological invasion or endangered species management, ecosystem restoration, species reintroduction, population viability analysis and human-wildlife conflicts (Hirzel et al., 2001; Hirzel et al., 2006). They are, often referred to as habitat suitability models, and consist of probability maps depicting the likelihood of occurrence of a species, whereby probability of species presence is assumed to be an index of habitat suitability (Store and Kangas, 2001).

In general, two habitat modelling approaches are distinguished: inductive and deductive habitat modelling approaches (Corsi et al., 2000; Stoms, 1992). Inductive habitat modelling generalizes the characteristics of locations where species occur to the rest of the management area, whereas deductive habitat modelling makes inferences from the general to a particular case. Deductive approaches are determined a priori, and try to predict the organisms by explicitly choosing habitat criteria which are believed to be important. In inductive approaches, habitat choices of a subset of the organisms are observed, and the chosen habitat characteristics are extrapolated to wider areas (Skidmore, 2002; Stoms, 1992).

These models usually suggest that distribution of species or communities follow a set of environmental factors which control them into particular areas (Guisan and Zimmermann, 2000). Three components are needed in the development of these models (Austin, 2002): (1) an ecological model which consists of the selection of environmental variables to be used, (2) a data model which determine how data will be collected, measured and estimated and (3) a statistic model which calibrates, analyses and evaluates the data. Most of statistical models rely on strong assumptions about the data and are responsible for the choice of data to collect

and in which format should be (e.g. presence/absence versus presence only) (Hirzel and Guisan, 2002).

Several models have been developed for this purpose (Guisan and Zimmermann, 2000; Skidmore, 2002). Guisan and Zimmermann (2000) group them into 7 categories: Multiple regression (and its generalised forms, e.g. GLM, GAM), Classification techniques, Environmental envelopes, Ordination techniques, Bayesian approaches, Neural networks and mixed approach (involving several methods).

Models using presence/absence mostly use multiple regression approaches with generalized techniques (GAM, GLM and regression tree (Guisan et al., 2002; Miller and Franklin, 2002) and classification tree (CT) (Miller and Franklin, 2002; Scull et al., 2005) and proved to be reliable (Guisan and Zimmermann, 2000). Moreover, several alternative modelling techniques were developed to include presence-only data without requiring absence data. These include environmental envelopes (BIOCLIM, e.g. (Beaumont et al., 2005), Genetic Algorithms for Rule-set Prediction (GARP, e.g. (Sanchez-Flores, 2007; Townsend Peterson and Cohoon, 1999), ecological niche factor analysis (ENFA) (Hirzel et al., 2002), Maximum entropy (MaxEnt) (Phillips et al., 2006) , etc.

The differences in these models appears in the integration of the response variable, selection and weighting and fitting of the individuals predictors and the interaction of variables as well as the format of the output (Lawler, 2006).

1.2. Problem statement

Rare species present characteristics of vulnerability to extinction and are more susceptible to habitat change (Santos et al., 2006). These characteristics include species with small population sizes and small geographic range sizes which inhabit areas with dense human population and which are subject to trade and have large body size, low reproductive success, high specialization, and low dispersal rate (Hawkins et al., 2000; Mace and Kershaw, 1997). Mountain gorillas, critically endangered species, exhibit most of these characteristics (Harcourt, 2002), so, vulnerable to habitat change.

However, mountain gorillas have been subject to loss of habitat which constrained them in high altitude exposing them to different environment and habitats of which some are unsuitable (Weber, 1983). This loss of habitat has more contributed to the decline of their population in the last century. The survival of these animals depends on the conservation of the integrity their habitat and any other change in their habitat could lead to their extinction. On the other hand, continuous modification of the habitat through illegal logging, fuel wood and non-timber forest products collection continue to increase pressure on their habitat (Gray and Kalpers, 2005). It is not known to what extent human signs recorded in the park can

influence the habitat; hence there is need in mapping and regularly monitoring the mountain gorilla habitat suitability.

Maps displaying the spatial configuration of suitable habitat can be an aid to define the actions required to manage their habitat appropriately. The development of Geographic Information Systems and remote sensing provides more practical these exercises, in terms of time as well as cost, as they offer the possibilities of minimizing field work and are easily updated as new information becomes available.

1.3. Research objectives

1.3.1. General objective

To explore the spatial relationship between the mountain gorilla habitat suitability and human impacts in the Virunga Volcanoes Mountains

1.3.2. Specific objectives

- To identify environmental variables significantly associated with mountain gorilla's habitat suitability in the Virunga Volcanoes Mountains;
- To model and map mountain gorilla habitat suitability in the Virunga Volcanoes Mountains;
- To assess the influence of human activities on the mountain gorilla habitat suitability in the Virunga Volcanoes Mountains.

1.4. Research questions

Research objective	Research question
To identify environmental variables significantly associated with mountain gorilla's habitat suitability in the Virunga Volcanoes Mountains;	• What are the environmental variables that better predict the habitat suitability of mountain gorillas?
To model and map mountain gorilla habitat suitability in the Virunga Volcanoes Mountains	• Which modelling algorithm predicts the habitat suitability best? • Where are the suitable habitats for mountain gorillas in the Virunga Volcanoes Mountains?
To assess human impact on the mountain gorillas habitat suitability	• To what extent do human impacts overlap with the mountain gorilla habitats suitability?

1.5. Research hypotheses

Ho: The chosen environmental variables do not predict better the suitable habitats of mountain gorillas than prediction by chance
Ha: The chosen environmental variables better predict the suitable habitats of mountain gorillas than prediction by chance

Ho: There is no difference in the accuracy of the suitable habitats maps predicted by different modelling algorithms
Ha: There is a difference in the accuracy of the habitats maps predicted by different modelling algorithms

Ho: Human impacts do not overlap significantly with the suitable mountain gorilla habitat
Ha: Human impacts overlap significantly with the suitable mountain gorilla habitat

1.6. Research approach

The first chapter talks about the general background of the study and gives the research problem, objectives and questions, the second chapter highlights the methods and materials used for this research. The third chapter presents the results of the analysis while the fourth chapter discusses the interpretations of results and their implications to the park management before concluding.

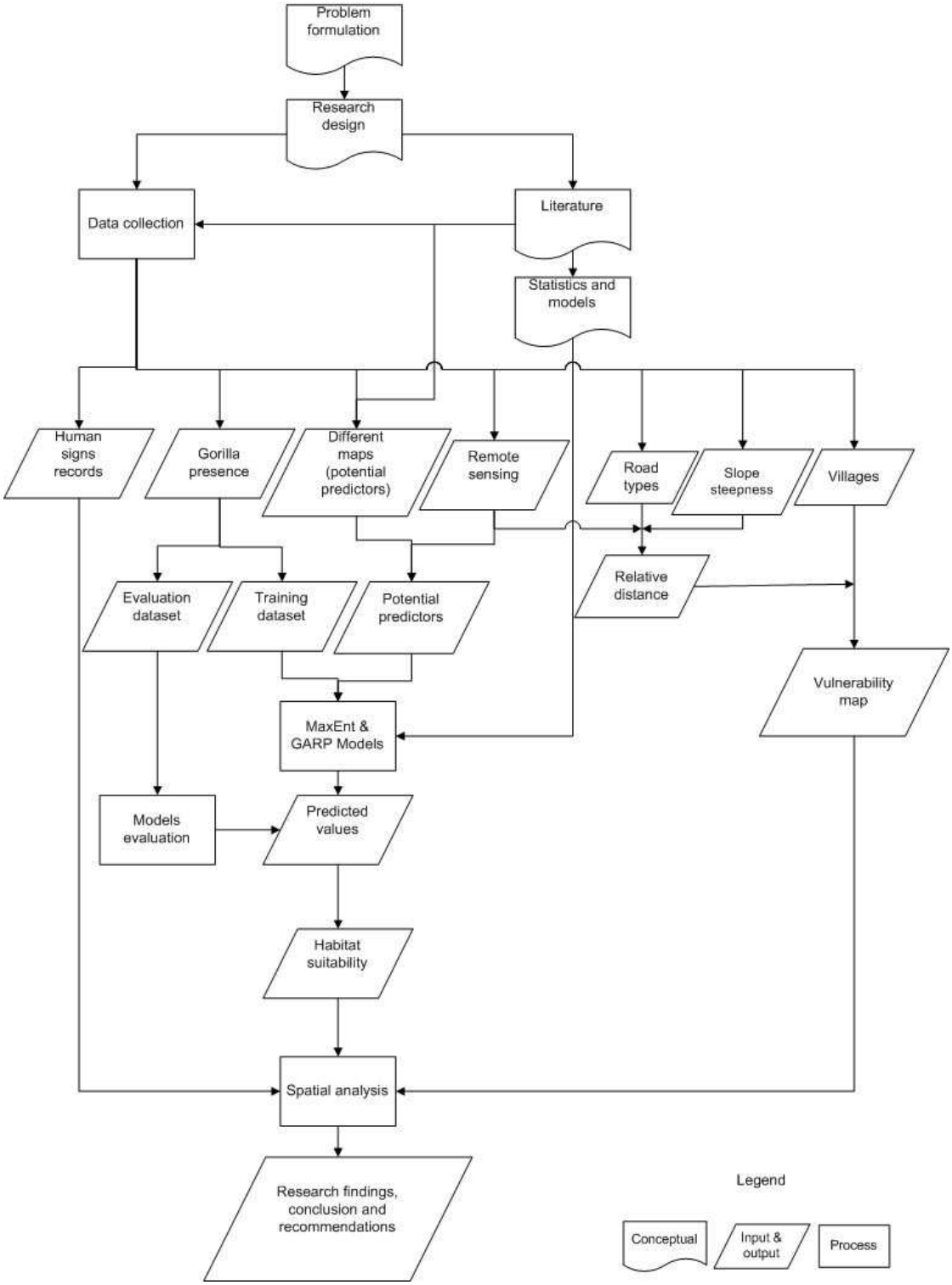

Figure 1-1: Flowchart of research process

2. Methods

2.1. Study area

This research is located in Central-East Africa in the Virunga Volcanoes Mountains which stretch out between 1° and 2°of latitude South and 29° to 30° of longitude East at the borders of Democratic Republic of Congo, Uganda and Rwanda and form an arc across the Albertine Rift Valley. It comprises three adjacent national parks (figure 2-1):

- In Democratic Republic of Congo, Parc National des Virunga (PNVi) designated as a World Heritage Site in 1979 and a World Heritage Site in Danger in 1994; and is managed by Institut Congolais pour la Conservation de la Nature (ICCN);
- In Rwanda, Parc National des Volcans (PNV) created in 1929 and designated as a Biosphere Reserve in 1983; and is managed by Office Rwandais du Tourisme et des Parc Nationaux (ORTPN); and
- In Uganda, Mgahinga Gorilla National Park (MGNP) which acquired National Park status in 1991 and is managed by Uganda Wildlife Authority (UWA).

The Virunga Volcanoes Mountains lies on six volcanoes respectively from East to West (figure 2-2): Muhabura (4 127 m), Gahinga (3 474 m), Sabyinyo (3 634 m), Bisoke (3 711 m), Karisimbi (4 507 m) and Mikeno (4 380 m) and range from 1 800 m to 4 507 m of altitude covering an area of approximately 450 km^2.

The vegetation is first characterised by altitude then by location factors such as aspect, slope and microclimates, from the mixed forest through the bamboo forest (2 300 – 2 600 m) to the afro-alpine vegetation (4 200 – 4 507 m) (Weber, 1987). The massif is rich in biodiversity some of which are endemic to the region others are rare or threatened and protected by international treaties such as the Convention on Migratory Species and Convention International on the Trade of Endangered Species (CITES), etc.

The region has a tropical climate altered by the altitude. The afro-montane vegetation characterised by high rate of evapotranspiration plays an important role in high level of rainfall registered in the region and playing also an important role of water catchment, releasing water slowly throughout the year for crops around the park. For instance, the park on the Rwandan side covers 0.6% of the country's area but provide 10% of water for Rwanda (Weber, 1987). The vegetation cover also plays a role of protecting land around the park from erosion and inundation. However, despite the high level of precipitation, there is almost no perennial river or stream due to high permeability of soils, consequently, the direct proximate environment of the park suffers from water shortage (Weber, 1987).

Geologically, the volcanic eruption of tertiary and quaternary have covered the region with successive layers of lava on Precambrian subbasement (Weber, 1987). The soils are essentially volcanic originated from the physical and chemical alteration of the lava and they are rich in humus and nutrients but poor in clay (Jost, 1987).

The region registers high number of population density which dominantly depends on subsistence agriculture. The fertile soils of the region allow growing a variety of crops; however, the production is limited by the problem of land parcelling (MINITERE, 2000; Weber, 1987) with more than 50 % without sufficient land to meet their basic needs (Lanjouw et al., 2001). In Uganda, 16 % of the population in this region is landless, and in north-western Rwanda, the figure is much higher (IGCP, 1996).

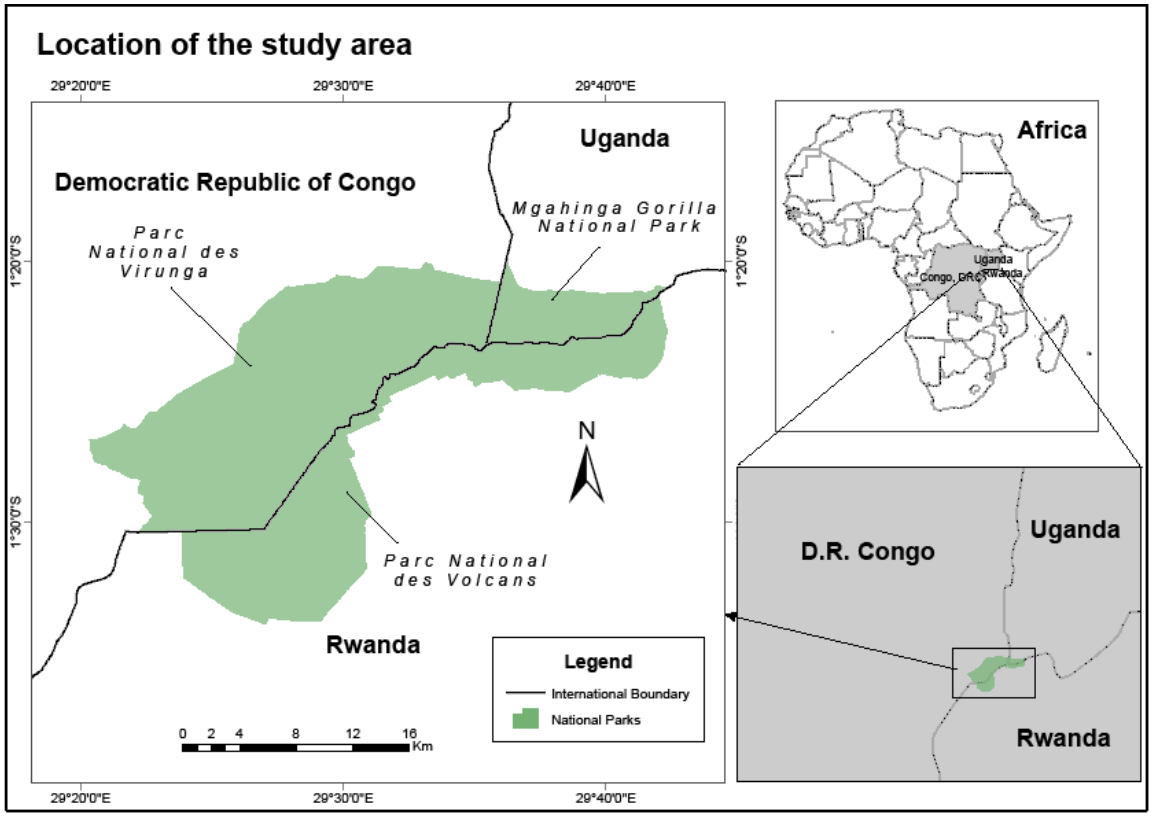

Figure 2-1: Location of the study area

2.2. Species occurence data

Mountain gorilla observation data were obtained from the Office Rwandais du Tourisme et des Parcs Nationaux (ORTPN) and the Karisoke Research Center (KRC). They consist of GPS point locations for different groups monitored regularly for the purpose of research and tourism. Two GPS points are collected every day: one in the nest and another one at noon when gorillas are resting. These groups have been regularly monitored from 1967 with the creation of the Karisoke Research Center by Dian Fossey. The use of GPS has started in the

1999-2000. The data were used directly to train and test the habitat suitability model. A total number of 3 377 occurrence records of 2006 were used and were split into two samples, one sample for training (75%) and another for evaluation (25%) (Appendix 7-1).

2.3. Environmental variables

2.3.1. Selection of environmental variables

Environmental variables were selected following the ecological processes that are believed to influence the Mountain gorilla distribution. Direct (precipitation, temperature) and resources (land cover as proxy for food and shelter) variables as well as indirect (topographic) variables were used in this study.

The table below illustrates the potential environmental variables:

Table 2-1: Potential environmental variables

Variable	Measurement unit	Source/resolution	Proxy
Elevation	m a.s.l	DEM (90 m)	Health hazard/risk, food availability
Slope (degrees)	degrees	DEM	Food, nesting places
Topographic position	Index	DEM	barriers
Solar radiation	WH/m^2	DEM	Nesting, food
Precipitation	mm/year	WorldClim	food availability, gorilla activity patterns, seasonality
Minimum temperature	^0C	WorldClim	Gorilla activity patterns, health
Maximum temperature	^0C	WorldClim	Gorilla activity patterns, seasonality
Average temperature	^0C	WorldClim	,, ,,
Land cover type	Categorical	Supervised classification Landsat TM 2003	Food quality, availability, shelter, Nesting sites

2.3.2. Topo-climatic variables

Topographic variables were derived from SRTM (DEM) of 90 m resolution. Before the extraction of the topographic derivates, the imperfections from the DEM were removed. These consist of remove the outliers and noise(Carlisle, 2005). In order to harmonise all input data with the same pixel resolution, the DEM was resampled to 30 m resolution. The resampled

technique used was the bilinear interpolation method (Phillips et al., 2006). Then topographic derivates (slope, topographic position, radiation) were calculated using ArcGIS® 9.2 spatial analyst extension.

The insufficient meteorological stations in the study area could not allow the interpolation of the climatic data (precipitation and temperature) which then were downloaded from WorldClim database (Hijmans, 2005) at a resolution of approximately 1 by 1 km resolution (30 arc second). These climatic data were downscaled to a resolution of 30 m resolution. Random points were generated in and around the study area and pixels values of both climatic (minimum and maximum temperature and precipitation) and topographic (elevation) values were extracted from the DEM and climatic surfaces with which a regression equation was developed and then used to calculate new surfaces of climatic variables with a fine resolution of 30 m. Then the new surfaces were clipped to fit the study area.

2.3.3. Vegetation related variables

2.3.3.1. Digital image classification and accuracy assessment

Vegetation types were derived from a Landsat TM image of 2003 which were classified with supervised classification maximum likelihood classifier algorithm in ERDAS IMAGINE® software. Ten classes were derived from the classification which consists of different vegetation types found in the Park. In order to do this classification, field work was carried out in the study area to collect ground truth points for image classification. Due to the fact that the study area is mountainous and the vegetation is firstly characterised by elevation, the sampling technique using transect was used in the existing trails from lower elevations to higher elevations representing all vegetation classes derived during image pre-processing prior to field work. 101 points were collected during the field work. Expert knowledge was used in selecting training points at a good distance from those visited in the fields work. Then all points collected during the field work were used to evaluate the classification results.

Due to the fact that it was only possible during field work to access the Rwandan side of the study area (figure 2-2), field data were collected in this area and the classification was extrapolated to the whole study area. The assumption is that due to the fact that the vegetation is characterised by altitude (Weber, 1983; Weber, 1987), the same land cover types at the same altitude should be the same on both sides of the volcanoes, though it needs to be verified later and collect more sample points on the other side in Democratic Republic of Congo and Uganda to improve the accuracy of the classification.

In order to smooth the classification result a low pass majority filter (3x3 windows) was applied the classification results. The accuracy of the image classification was assessed by the technique of the overall accuracy which is the proportion of the correctly classified points and the total number of sample points and Kappa coefficient “k^”. Kappa statistics is an estimate of measure of overall agreement between image data and the reference data. Its values

(coefficients) are between 0 and 1 where kappa of 1 represents perfect agreement and value of 0 being no agreement. It is grouped into three categories (Congalton, 1996): values above 0.80 represents strong agreement, values between 0.4 and 0.80 represents moderate agreement while values below 0.4 represents poor agreement.

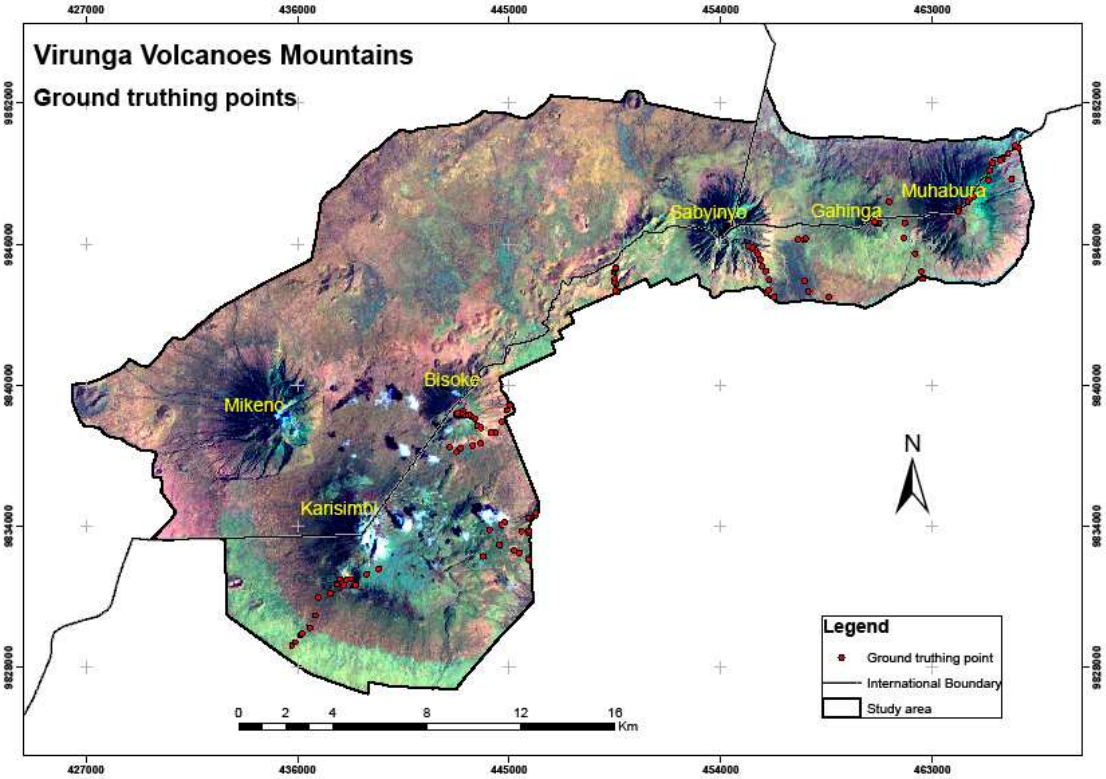

Figure 2-2: Ground truth points used in the classification overlaid on the 2003 Landsat TM image (4, 5, 2)

2.4. Screening environmeantal variables

Statistical analysis was carried out to test the correlation and collinearity among the variables. Correlation among variables leads to bias in the prediction as well as the contribution of each variable in the model, thus correlated variables should not be used in the model (Fielding and Bell, 2002; Pearson et al., 2007). Collinearity occurs when one or more variables are exact or near exact linear functions of other variables in the data set.

The variables were screened by the following methods:

- Pearson's product-moment correlation among the continuous variables
- Pairwise scatter plots and linear regression among continuous variables
- Jackknife test of variable importance of MaxEnt experimental model. The jackknife assessment excludes one variable at a time and recreates the model to determine the relative contribution of the predictor variable to the habitat suitability. It also takes each variable separately to determine whether it alone contributes significantly to the model.
- Chi square goodness-of-fit test for vegetation types selection

2.5. Habitat suitability modelling approach

Two different modelling algorithms were used to predict the probability of species occurrence onto environmental variables. Both algorithms use presence-only data and are dedicated to make predictive map within the study area. The selected algorithms are MaxEnt (Phillips et al., 2006) and GARP (Stockwell and Peters, 1999).

2.5.1. Maximum Entropy (MaxEnt) modelling

Maximum entropy is a well established statistical technique which makes prediction from incomplete information (Jaynes, 1957; Phillips et al., 2006). Its advantage lies in the fact it requires presence only data to make predictions from species observations and environmental layers that limit the species occurrence (Phillips et al., 2006). The principle of maximum entropy (that is most spread out or closest to uniform) places no constraints on the probability distribution of the species or habitat assuming that each feature (constraint) has the same mean in the approximated distribution as in the empirical observations (known species occurrences). MaxEnt start by assuming a uniform probability distribution and iteratively updates an algorithm that describes the habitat distribution based on computed weights of all the features used. As the algorithm is getting updated, the gain exponentially increases at suitable location with highest entropy and the constraining criteria. To avoid an overfitting of the model a regularization option is available that controls the iterative gain. For more detail on MaxEnt for habitat modelling see (Phillips et al., 2006).

The MaxEnt software version 3.1.0 (Robert, 2007) was used in this study. MaxEnt requires environmental variables to be in ASCII grid format and the species occurrences as SCV file. The input data (environmental variables and species occurrence) were prepared in ArcGIS 9.2® software where the environmental layers were georeferenced to the same coordinate system and converted to ASCII grid files and species occurrences in the same coordinates as environmental layers and the DBF file was converted to CSV file using Microsoft excel. The parameters were set as follows: regularization multiplier = 1, maximum iterations = 1000, convergence threshold = 10^{-5}, maximum number of background pixels = 10 000. Selection of ‘features’ (environmental variables or functions thereof) was also carried out automatically, following default rules dependent on the number of presence records. MaxEnt assigns a probability of occurrence to each cell in the study area. Because these probabilities must sum to 1, each cell’s probability is usually extremely small, making model output difficult to interpret. We therefore present model predictions as cumulative probabilities, wherein the value of a given grid cell is the sum of that cell and all other cells with equal or lower probability, multiplied by 100 to give a percentage (Phillips et al., 2006). The output format was later imported in ArcGIS 9.2® software. The response curves as well as the jackknife test of variable importance were carried out.

2.5.2. Generic Algorithm for Rule-based Prediction (GARP)

GARP is machine learning approach mostly designed to predict potential distribution of species within their environmental characteristics (Anderson et al., 2003; Peterson and Cohoon, 1999; Stockwell and Peterson, 2003). The GARP algorithm works in an iterative process of rule selection, evaluation, testing and incorporation or rejection according to their significance in the model to give a binary prediction where positive rules produce suitable habitat and negative rules unsuitable habitat (Peterson and Cohoon, 1999; Phillips et al., 2006). More information about the GARP are found in (Stockwell and Noble, 1992; Stockwell and Peters, 1999).

The same input data as in MaxEnt modelling were used as also GARP requires ASCII format as environmental layers and CSV file for species occurrence. All rules in GARP (atomic, range, negated range and logistic regression rules) were selected and used in the modelling. The model was run 100 times with convergence limit of 0.01 and 1000 maximum iterations. Best subset selection was performed and the models of 10 % of extrinsic hard omission threshold were selected. Contrary to the MaxEnt prediction which is continuous, GARP gives a binary prediction (values of 0 or 1). Best subset was chosen to select ten best models close to the median of the predicted area. This method favours predictions with low omission error whilst removing models that overfit or predict hardly large predicted areas (Pearson et al., 2007). After selecting the best-subset predictions, they were combined to give a continuous prediction of values from 0 to 10 with an increase in increments of 1.

2.6. Evaluation of the habitat suitability models

Different techniques to assess the accuracy of spatial habitat predictive models have been discussed in Skidmore (1999) and Corsi et al. (2000). They consist of how well they correspond to the reality (de Leeuw et al., 2002). In this study, Receiver Operating Characteristics (ROC) plot (Hanley and McNeil, 1982) and its Area Under the Curve (AUC) were used to assess the predictive ability of the models.

2.6.1. Receiver Operating Characteristics

A ROC plot is produced by plotting the sensitivity values, the true positive fraction against 1-specificity, the false-positive fraction for all available probability thresholds(Fielding and Bell, 2002). A ROC curve that maximizes sensitivity for low values of the false-positive fraction is considered a good model and is quantified by calculating the Area Under the ROC Curve (AUC). The AUC is a threshold-independent measure and can be used as a measure of the model's overall performance and has values usually ranging from 0.5, the model which predicts accurately only 50% of the time, essentially at random (no discrimination), to 1.0 (perfect discrimination) (Engler et al., 2004; Metz, 1978). AUC is classified following Hosmer and Lemeshow (2000) as follows: AUC = 0.5, no discrimination, 0.7 < AUC <0.8, acceptable, 0.8 < AUC < 0.9, excellent and AUC > 0.9, outstanding.

While ROC curves are typically associated with presence-absence modeling, here the analogue for absence is background points (Phillips et al., 2006). The AUC (Area Under Curve) was thus developed using background data instead of absence data, and can be interpreted as a measure of the ability of the algorithm to discriminate between a suitable environmental condition and a random analysis pixel (background), rather than between suitable and unsuitable conditions, as an AUC developed with measured absences is interpreted (Phillips et al., 2006).

2.7. Reclassification of habitat suitability maps

To be able to reclassify the habitat suitability maps into manageable habitat classes, first of all, a threshold that distinguishes the suitable habitat from the unsuitable ones has to be determined and above which the model is considered to be a prediction of presence (Pearson et al., 2007), Many techniques have been used to select this threshold (Liu et al., 2005a), but most of them depending on balancing false-positive and false negative predictions normally in presence-absence data models.

Here, we selected the lowest presence threshold which is the lowest predicted value associated with any of the observed presence records (Pearson et al., 2007). This threshold has ecological interpretation by identifying areas that are at least as suitable as those where the species presence has been recorded (Pearson et al., 2007) which is in accordance of this study.

The habitat suitability was reclassified into three classes; the unsuitable conditions lower the threshold and the suitability conditions were divided into two classes: highly suitable and suitable.

2.8. Human impact on habitat suitability

2.8.1. Indirect human impact on mountain gorilla habitat suitability

Indirect human impact consists of illegal activities carried out by human population neighbouring the park. Data on illegal activities in the park are collected regularly by park rangers using Ranger Based Monitoring tool (Gray and Kalpers, 2005), data collection protocols developed for harmonization and standardization of data. According to the data, illegal activities are classified into 6 main categories: Snares, bamboo and wood cutting, water collection, honey collection, human presence (tracks, camps), grazing and dogs.

Table 2-2 gives a summary of human signs registered in the park (Rwandan side) during year 2006.

Table 2-2: Human signs registered in the park for 2006

Human signs	Number
antelope snares	902
bamboo/wood collector	389
beehives	188
dogs	17
grazing	10
honey collectors	5
illegal human tracks	1 625
poachers	6
water collectors	833

Data on indirect human impact of the previous years (2004 and 2005) were also examined in relation to gorilla habitat utilization as it is expected that areas with continuous human impact are avoided by mountain gorillas. Kernel density estimator (Powell, 2000) was calculated for both gorilla and human impact distribution. Kernel density estimator is important to understand the spatial utilization of an area by gorillas and human populations and 50% kernel density estimator of each was considered as the core area used by gorillas and human impact.

2.8.2. Vulnerability analysis

The intensity or frequency of human activities on wildlife distribution and their habitat can have positive or negative effects and are function of how close people are to the their locations and the infrastructure used (de Leeuw et al., 2002). To assess the potential impact of human population on the park, an accessibility model was constructed in terms of travel time which is function of distance from settlements, land cover types, type of road used and slope steepness (figure 2-3). The accessibility model shows areas which potentially are likely easy to access and likely vulnerable to more human impact and areas of low impact in areas which are classified as difficult to access. Therefore, while the accessibility model gives potential impact on the park, it would be reasonable to add the motivation of the people to go in the park. Motivation would be defined as the willingness to go in the park based on unsatisfied need of a resource e.g. wood shortage, water or meat as a result of the availability and demand of the resource. However, the absence of such data didn’t allow including the motivation in the modelling of the human impact on the park.

In addition to the impact on the park as a function of the accessibility model, comparisons of actual human impact recorded in the park are made to the vulnerability areas and to the mountain gorilla habitat suitability and utilisation.

The accessibility model was adopted from Toxopeus (1997). Different factors related to accessibility were taken into account for the construction of this model: road types, land cover, slope steepness and location of the villages in the study area.

1. accessibility calculation according to road infrastructure:
   Roads types of the study area were obtained from ORTPN and KRC and were classified into 3 types with a different travelling speed for each (Appendix 7-5). Then a raster map representing the travelling speed by road type was created.
2. accessibility calculation according to land cover types:
   The land cover types were classified from a Landsat image of 2003 including the area outside the park until the location of the villages as the land cover types influence also the walking speed. Then it was reclassified into different expected walking speed (Appendix 7-5) based on the estimation from the field work conducted in September - October 2007 and a raster map representing travelling speed by each land cover type was created.
3. accessibility calculation according to slope steepness:
   The slope steepness influences the accessibility to different parts of the park as it influences the travelling speed as well as travelling time. The steeper the slope, the less the travelling speed is. However, the slope steepness has to be classified in regard to the expected influence on the travelling speed which is slope correction factor (Appendix 7-5)
4. Calculation of travel speed map as function of road speed map, land cover speed map and slope factor which gives a continuous map where high values increase, so do the travelling speed therefore the distance will be shorter compared areas with low speed values. For that reason, the values of the travel speed map should be inversed to get low values for easy travelling conditions and high values for difficult travelling conditions.
5. Calculation of distance map from each village taking into account the travelling condition map (inversed values of travelling speed map) as weight. The result is a map showing accessibility (distance in meters) to the park from each village in the study area. The map is converted to travelling time map assuming that under normal conditions (with no resistance) walking time is 6 km per hour. This means that the map expresses the time in terms of hours that will take from the settlements to reach a certain point in the park where: A pixel with value 1 (no resistance) is assumed to be 6 km per hour, so the distance of the pixel with value 1 is 1 x 30 meters (pixel size) and the travelling time will be 30/6000 m (6 km) = 0.005 hours.
6. Reclassification of the travelling time map into vulnerability zones: the lesser the time to access the park the higher the vulnerability of that point in the park. The classes are categorized as follows:
   - Less than one hour: highly vulnerable
   - Between one hour and two hours: vulnerable
   - Between two hours and three hours: moderately vulnerable
   - More than three hours: less vulnerable

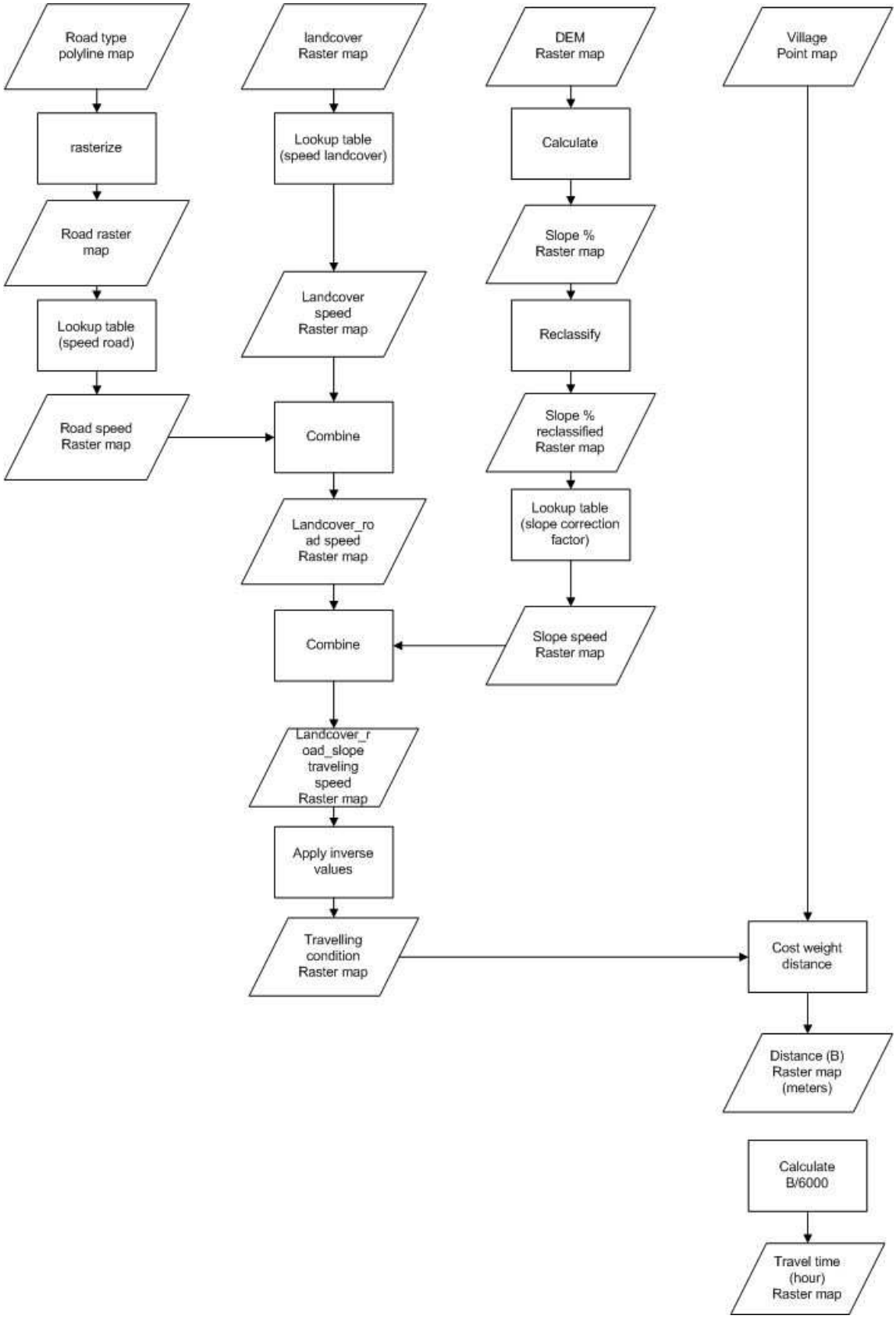

Figure 2-3: Flowchart of the accessibility model

2.9. Software used

Table 2-3 gives a summary of software used for processing, analysis and reporting in this research.

Table 2-3: Software used in this study

Software	Used for:
ArcGIS 9.2	• Data preparation • Spatial analysis • Map production • Sampling (Hawth's Analysis Tools) • Kernel home range (Hawth's Analysis Tools) • Accessibility modelling
ERDAS IMAGINE 9.1	• Image classification
MAXENT 3.1	• Habitat suitability modelling
GARP 1.6 Desktop	• Habitat suitability modelling
SPSS 15	• Statistical analysis • ROC curves plots
R	• Scatterplots matrix
Microsoft Excel 2003	• Data preparation • Statistical analysis
Microsoft Visio 2003	• Flowcharts
Microsoft Word 2003	• Reporting

3. Results

3.1. Mountain gorilla habitat suitability

3.1.1. Screening environmental variables

To test the correlation among the environmental variables Pearson correlation, scatterplots and linear regression were performed. From the visual assessment of pairwise scatterplots (appendix 7-2) and from linear regression (appendix 7-3) and the Pearson correlation test (table 3-1), some variables are inter-correlated and show collinearity among them. The inter-correlated variables were eliminated. This is the case for climatic variables which are highly correlated among themselves and with altitude. Therefore altitude was used as proxy for the eliminated climatic variables. The variables showing a low contribution to the MaxEnt experimental model (figure 3-2) were also eliminated. This is the case for topographic position (topo).

Table 3-1: Pearson correlation among continuous environmental variables

	Elevation	Slope	topo	prec	tmin	tmax	tav
Elevation	1						
Slope	0.44(**)	1					
Topographic position (topo)	0.26(**)	0.15(**)	1				
Precipitation	**0.99**(**)	0.44(**)	0.27	1			
Minimum temperature (tmin)	**-0.99**(**)	-0.44(**)	-0.27(**)	**-0.99**(**)	1		
Maximum temperature (tmax)	**-0.99**(**)	-0.44(**)	-0.27(**)	**-0.99**(**)	**0.99**(**)	1	
Average temperature (tav)	**-0.99**(**)	-0.44(**)	-0.27(**)	**-0.99**(**)	**0.99**(**)	**0.99**(**)	1
Radiation	0.43(**)	-0.58(**)	0.09(**)	0.43(**)	-0.43(**)	-0.43(**)	-0.43(**)

** Correlation is significant at the 0.01 level.

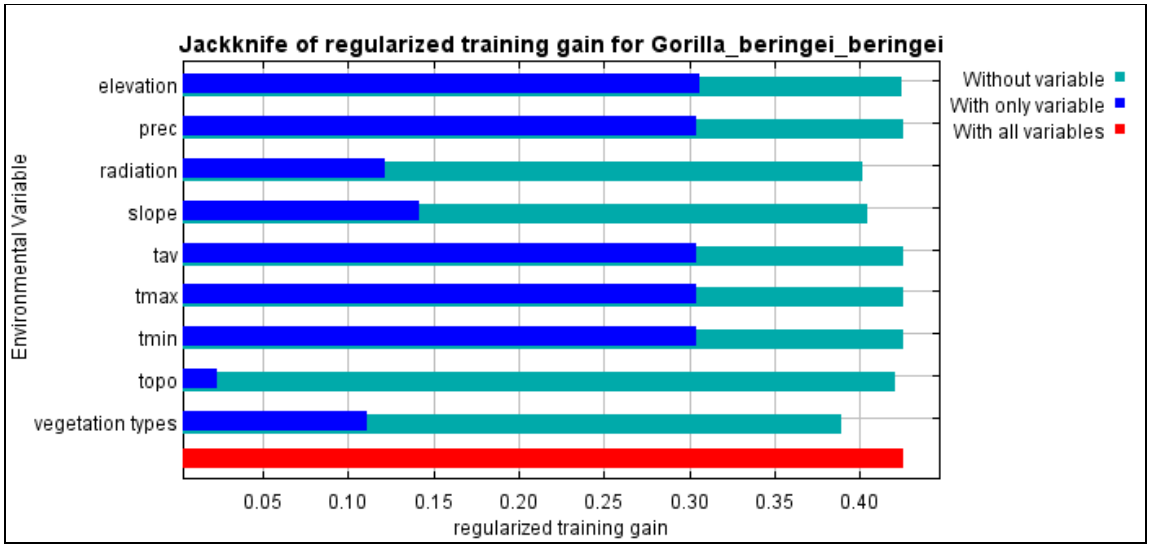

Figure 3-1: Jackknife analysis of MaxEnt experimental model with all variables

From this jackknife test results (figure 3-1); the environmental variable with highest gain when used in isolation is elevation, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is vegetation, which therefore appears to have the most information that isn't present in the other variables, followed by radiation and slope. The climatic variables (prec, tav, tmax and tmin) have the same gain in the model and follow the elevation when they are used each alone or omitted. But this should be interpreted with caution because of their correlation among themselves and with elevation.

Table 3-2 gives a heuristic estimate of relative contributions of the environmental variables to the MaxEnt model. As with the jackknife, variable contributions should be interpreted with caution when the environmental variables are correlated.

Table 3-2: Contribution of environmental variables to the experimental MaxEnt model

Environmental Variable	Contribution (%)
Elevation	49.2
Radiation	13.2
Vegetation	10.4
Annual precipitation (prec)	10.3
Slope	9.8
Average temperature (tav)	5.7
Topographic position (topo)	1.4
Maximum temperature (tmax)	0
Minimum temperature (tmin)	0

3.1.1.1. Vegetation cover types selection by Mountain gorilla

Results of the image classification are shown in figure 3-2. The classified land cover classes are: Bamboo forest, *Hagenia-Hypericum* forest (stands for *Hagenia abyssinica* and *Hypericum revolutum*), Brush ridge, Mixed forest, *Neobutonia* forest (stands for *Neobutonia macrocalyx*), Alpine meadow, Meadow/savannah, Herbaceous, *Mimulopsis* and Water. White areas indicate clouds on the image.

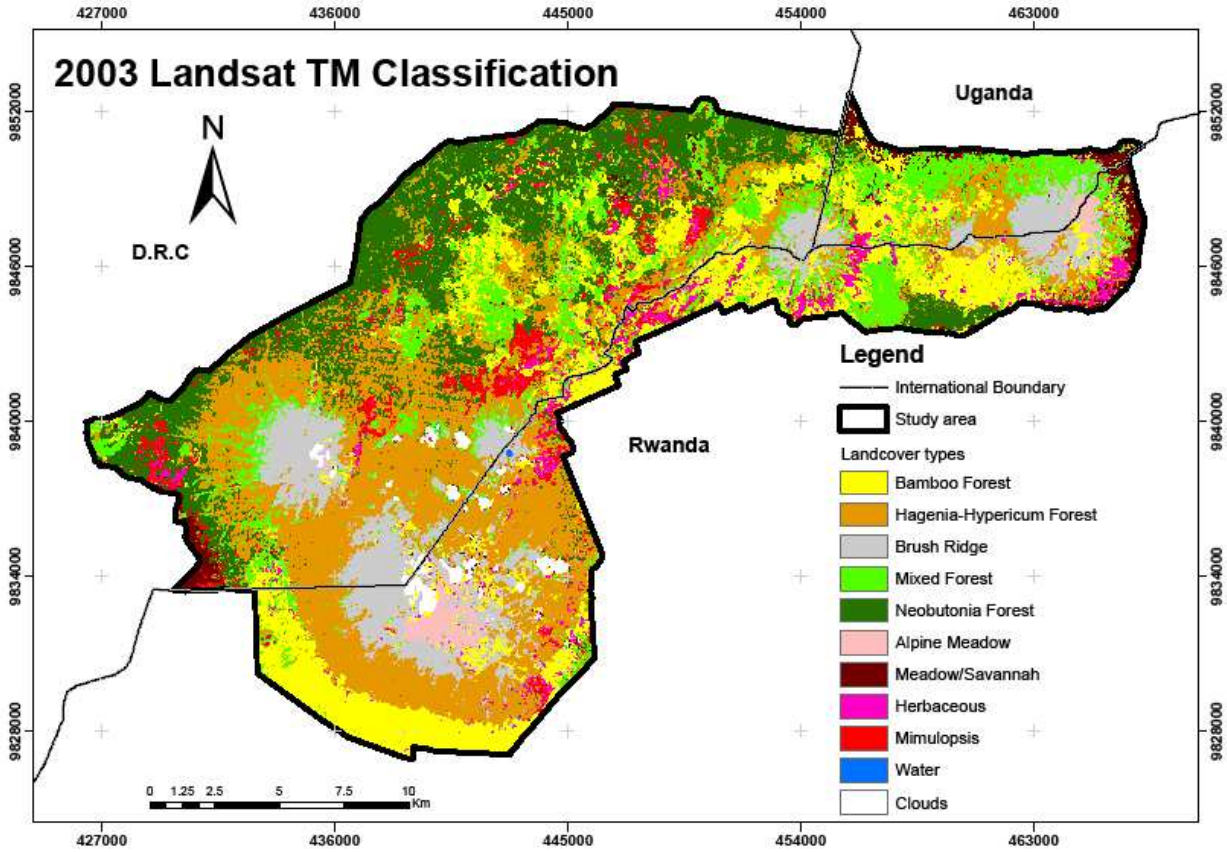

Figure 3-2: The classified image of Landsat TM 2003

101 field ground truthing points were used to assess the accuracy of the image classification. The classification accuracy is shown in the confusion matrix (table 3-3):

Table 3-3: The confusion matrix for accuracy assessment

Class Name	*Reference Totals*	*Classified Totals*	*Number Correct*	*Producers Accuracy (%)*	*Users Accuracy (%)*	*Kappa (K^) for each category*
Bamboo forest	15	19	13	86.7	68.4	0.63
Hagenia-Hypericum forest	21	24	16	76.2	66.7	0.58
Brush ridge	19	16	15	78.9	93.7	0.92
Mixed forest	17	12	10	58	83.3	0.80
Neobutonia forest	2	2	2	100	100	1
Alpine meadow	9	8	8	88.9	100	1
Meadow/savannah	4	5	4	100	80	0.80
Herbaceous	10	8	6	60	75	0.72
Mimulopsis	2	4	2	100	50	0.49
Water	2	2	2	100	100	1
Totals	101	101	78			
Overall Classification Accuracy = 77.23%				**Overall Kappa statistics = 0.73**		

Mountain gorillas' locations were overlaid on the vegetation cover types to check the importance of vegetation types on mountain gorillas' distribution. Figure 3-3 shows the proportion of mountain gorillas' observations frequency in different vegetation cover types. The most frequent selected vegetation type was the *Hagenia-Hypericum* forest (40%) followed by bamboo forest (20%) and herbaceous (14%). The least selected vegetation types are alpine meadow, meadow/savannah, and brush ridge.

To test whether this vegetation types selection was due to chance, a chi square goodness-of-fit test was performed on gorillas vegetation types use by vegetation types availability (area) and showed significant differences between overall vegetation availability and use when considering all vegetation types (χ^2 = 1833.11, d.f. = 8, $p < 0.001$) and allow to conclude that vegetation type selection is not random.

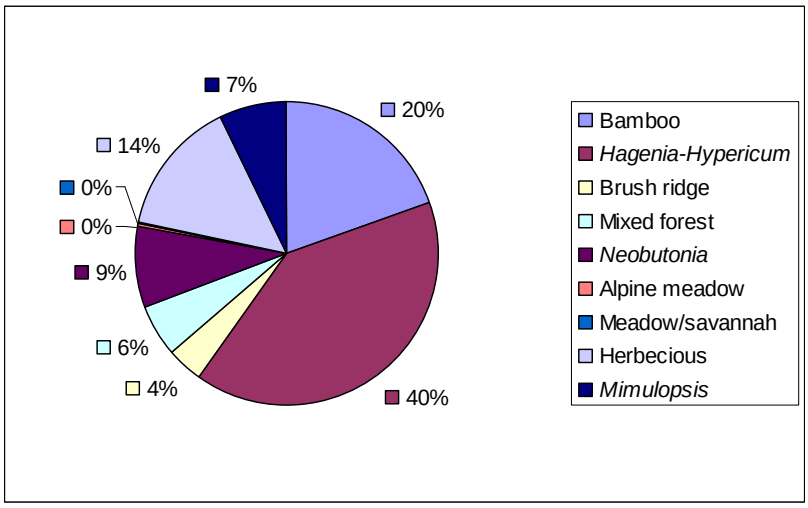

Figure 3-3: Frequency of observations of mountain gorillas in different vegetation cover types

3.1.2. MaxEnt model

This section presents the results of MaxEnt modelling. MaxEnt model gives three important results: the predictive map, jackniffe test of variables importance and the relative contribution of environmental variables to the MaxEnt model.

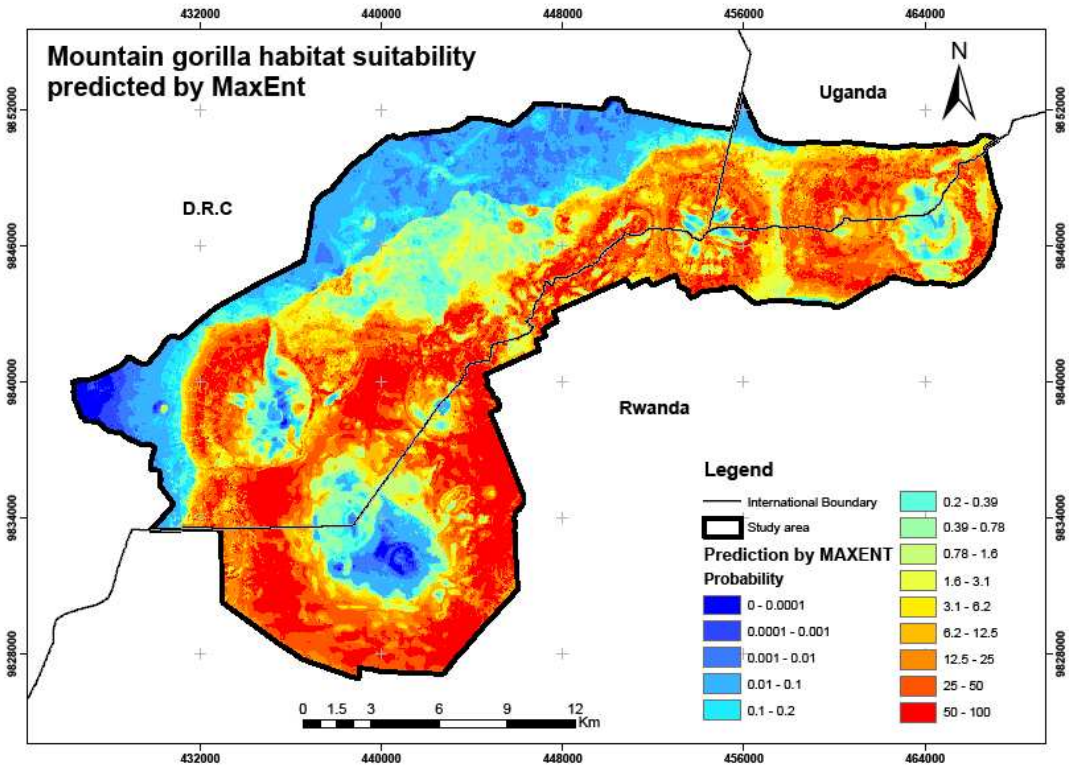

Figure 3-4: Probabilistic predictive map of mountain gorilla habitat suitability by MaxEnt

This is the projection of the MaxEnt model for Gorilla onto the environmental variables. Warmer colours show areas with better predicted conditions.

From the visual inspection of the predictive map by MaxEnt, better predicted conditions are found on the slopes around and between the volcanoes cones. Low habitat suitability predictions are observed in high altitudes on the slopes of the volcanoes summits. These areas correspond to the areas with less observation of gorillas. Low relative suitability is also observed on the Congo side in low altitude probably due to the fact that observation used in this study are located relatively in high altitude compared to this area.

Figure 3-5 shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation was elevation, which therefore appears to have the most useful information by itself. It is followed by slope then radiation and vegetation types. The environmental variable that decreases the gain the most when it is omitted is again elevation, which therefore appears to have the most information that isn't present in the other variables and is followed by radiation then vegetation types and slope.

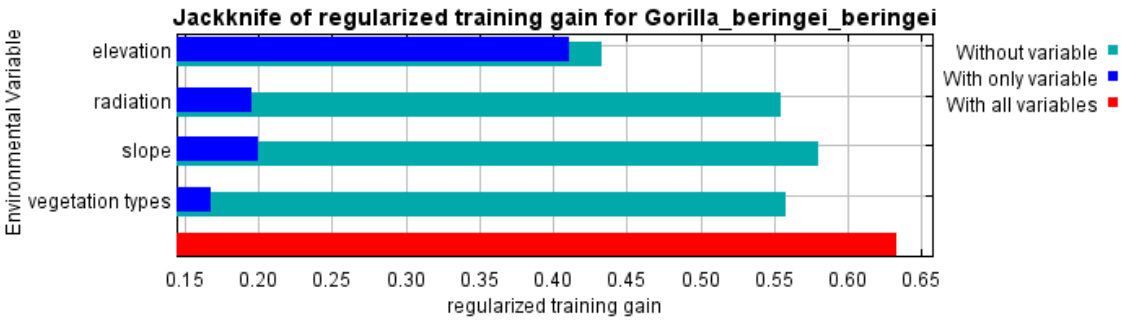

Figure 3-5: Jackknife test of variable importance for training dataset

Table 3-4 gives a heuristic estimate of relative contributions of the environmental variables to the MaxEnt model. Elevation was found to be the most important and contributes more to the model with 57.9% followed by solar radiation, vegetation types and slope. Response curves indicating the influence of the variables on the MaxEnt prediction are found in appendix 7-4 for example that elevation is well supported between 1800 m and 3500 m, radiation and slope increase as the prediction gets better until they reach an optimum value.

Table 3-4: Relative contributions of the environmental variables to the MaxEnt model

Variable	Contribution (%)
Elevation	57.9
Radiation	17.1
Vegetation types	13.2
Slope	11.8

3.1.3. GARP model

This section gives the results from GARP modelling. The same pattern as in MaxEnt are observed with better prediction conditions on the slopes around and between the volcanoes cones and low probabilities in high and lower elevations of the study area. However, GARP did not predict areas in the central part of the study area which are predicted by MaxEnt (figure 3-6).

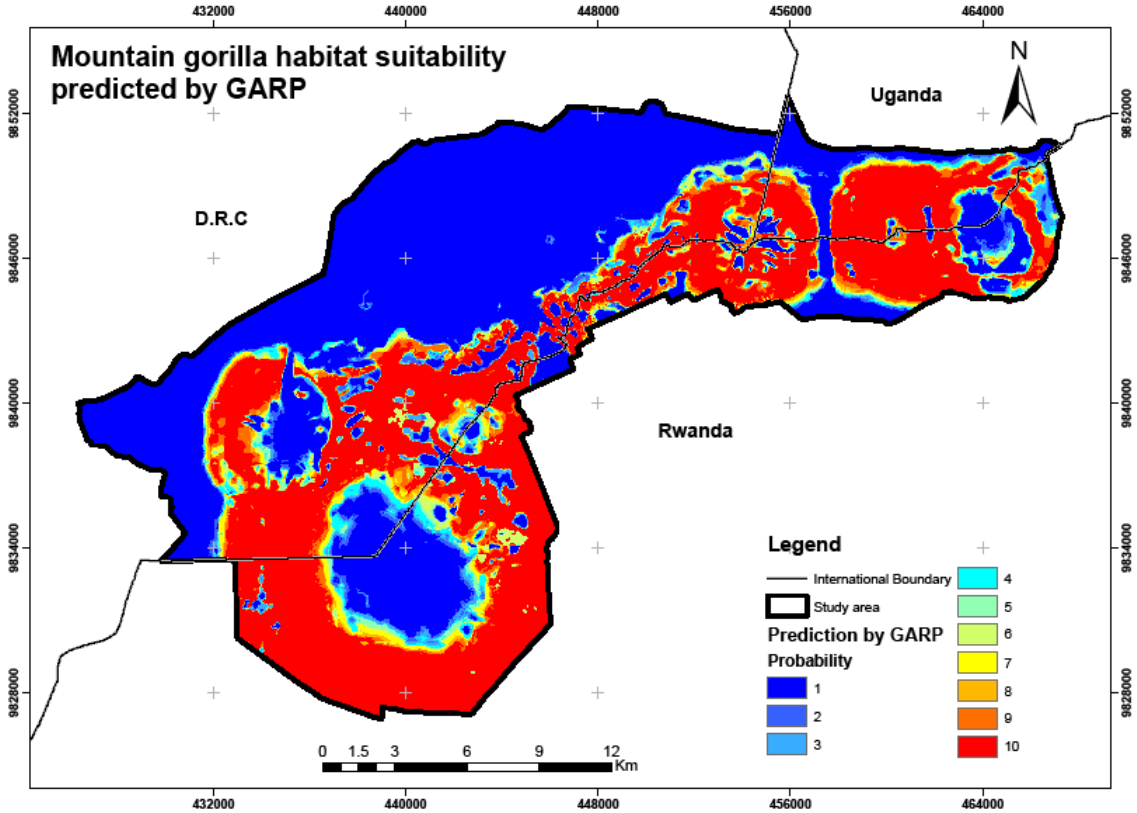

Figure 3-6: Probabilistic predictive map of Mountain gorilla habitat suitability by GARP
This is the projection of the GARP model for Gorilla onto the environmental variables. Warmer colours show areas with better predicted conditions.

3.1.4. Validation and comparison of the habitat suitability models

Both algorithms MaxEnt and GARP performed better than random to predict mountain gorilla habitat suitability ($p < 0.0001$). Table 3-5 gives the comparison of the accuracy assessment of the performance of the different modelling algorithms by Area Under the Curve (AUC) on both training and test dataset and figure 3-7 shows the comparison of the ROC curves of MaxEnt and GARP on both training and test dataset. For both algorithms, the test dataset gives better accuracy than the training though not very different. However MaxEnt performs better over GARP. MaxEnt prediction is classified as excellent while GARP is acceptable.

Table 3-5: Results of the ROC curves for mountain gorilla habitat suitability predicted by MAXENT and GARP for test and training dataset

					95% CI	
	Algorithm	**AUC**	**SE**	***p***	**Lower**	**Upper**
Test data	MaxEnt	**0.89**	0.006	<0001	0.880	0.905
	GARP	0.80	0.010	<0001	0.780	0.817
Training data	MaxEnt	**0.87**	0.004	<0001	0.860	0.876
	GARP	0.76	0.006	<0001	0.752	0.775

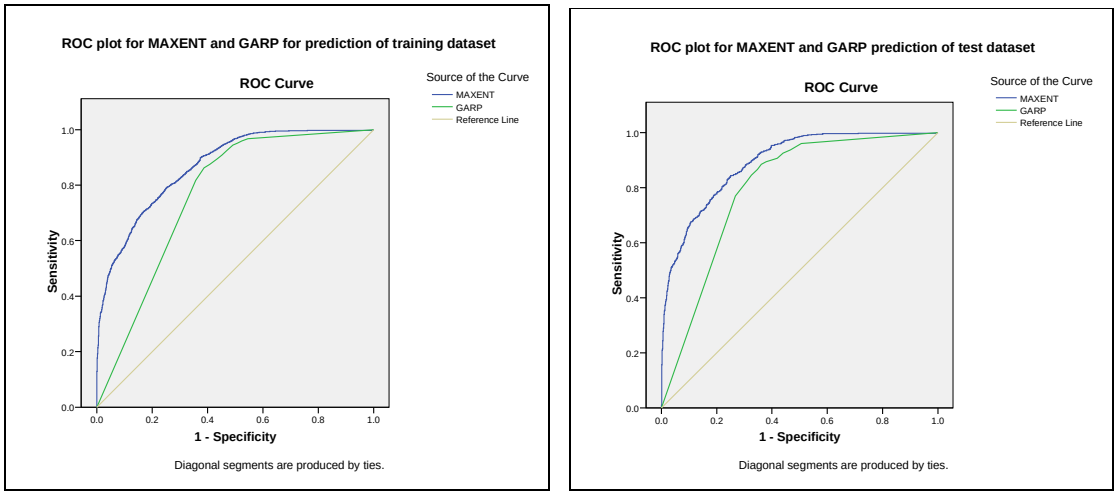

Figure 3-7: Comparison of ROC curves of MaxEnt and GARP on training (left) and test (right) dataset

The visual inspection of the two ROC plots shows that both models discriminate optimally suitable habitat from the unsuitable however some differences are noticed, which are the sources of the difference in the accuracy of the models. The differences are more pronounced at the left in the lower parts of the graphs and reduce considerably in the upper parts. These differences are reflected on the appearance of the predictive maps as the differences are observed in lower predictions contrary to better predictions where the same patterns appear for both modelling algorithms.

3.1.5. Reclassification of the habitat suitability map

The most accurate predictive map was reclassified into three habitat suitability classes using the lowest presence threshold. MaxEnt result was used to reclassify the habitat suitability map. It can be observed from the suitability map (figure 3-8) that areas of high suitability are more concentrated in the western part of the study area on the gentle slopes and between the volcanoes Bisoke, Karisimbi and Mikeno. High suitable habitats are also found between Bisoke and Sabyinyo, on the foot of Sabyinyo volcano and around Gahinga volcano. A

continuous trend from the suitable habitats to highly suitable habitats is observed and vice-versa.

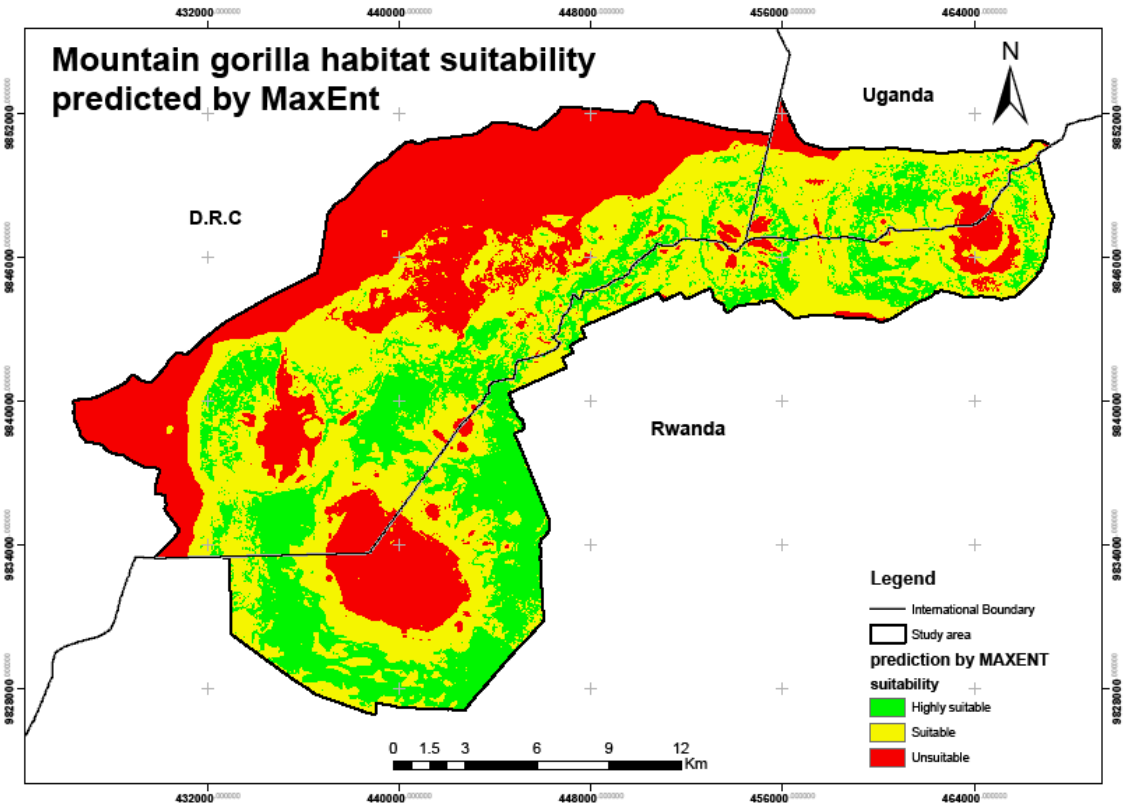

Figure 3-8: Habitat suitability reclassified into three categories

3.2. Influence of human impact on mountain gorilla habitat suitability and utilization

3.2.1. Indirect human impact on mountain gorilla habitat suitability

Mountain gorilla habitat suitability map was compared to human signs recorded in the park. Table 3-6 gives the summary of human signs and gorilla observations found in each habitat suitability category:

Table 3-6: Summary of human signs and gorillas overlaid on habitat suitability map

Suitability	Human sign	% (corrected by area)	Frequency of gorilla observations	% (corrected by area)
High Suitable	2093	47	3297	66
Suitable	1434	44	1078	30
Unsuitable	223	9	130	4

From the table above, it can be observed that suitability areas containing more gorillas are likely also to have more human signs. Suitable conditions have 96% of gorillas' observations and 91 of human signs. The positive correlation is found between the number of human signs and gorilla in the suitability classes (r = 0.84).

However, when using the spatial locations of gorillas and human signs, this trend changes. Spearman's Rho correlation was used to see the relationship between the 50%, 75% and 95% of the mountain gorilla kernel density estimators with the number of all and each of the human impact that fall into those kernels density estimators. Table 3-7 shows the correlation results. It can be observed that mountain gorilla distributions are negatively correlated with the combined illegal human signs and most of the illegal signs are also negatively correlated with the mountain gorilla distribution. It is important to notice that illegal activities falling outside the kernel distribution contours are not taken into account in the correlations as they are believed not to influence directly the gorilla distribution. This is the case for human signs in the west of Karisimbi and on Muhabura volcano.

Table 3-7: Correlation matrix between human signs against gorilla locations in 50, 75 and 95% kernel probability distribution

Illegal human signs	Gorilla locations
antelope snares	-0.722
bamboo/wood collector	-0.786
beehives	-0.788
dogs	0.117
honey collectors	-0.639
illegal human tracks	-0.596
poachers	0.163
water collectors	-0.718
Total	**-0.78304**

To illustrate the negative correlation between human impact and gorillas' locations, the core areas of gorilla locations and human signs were overlaid on the habitat suitability map (figure 3-9). It can be visualized that both core areas of gorilla's location are situated in suitability conditions areas (as already seen above in this section) but spatially are located in different areas and have a small overlap between them (only 20% overlap). As should be expected that human impact of the previous years influence the distribution of current gorilla distribution, The investigation of human impacts of the previous years (2004 and 2005) shows also a significant overlap between the core areas of human impacts (figure 3-10) and with also a very small overlap with "current" gorilla locations (2004: 4 %; 2005: 6%).

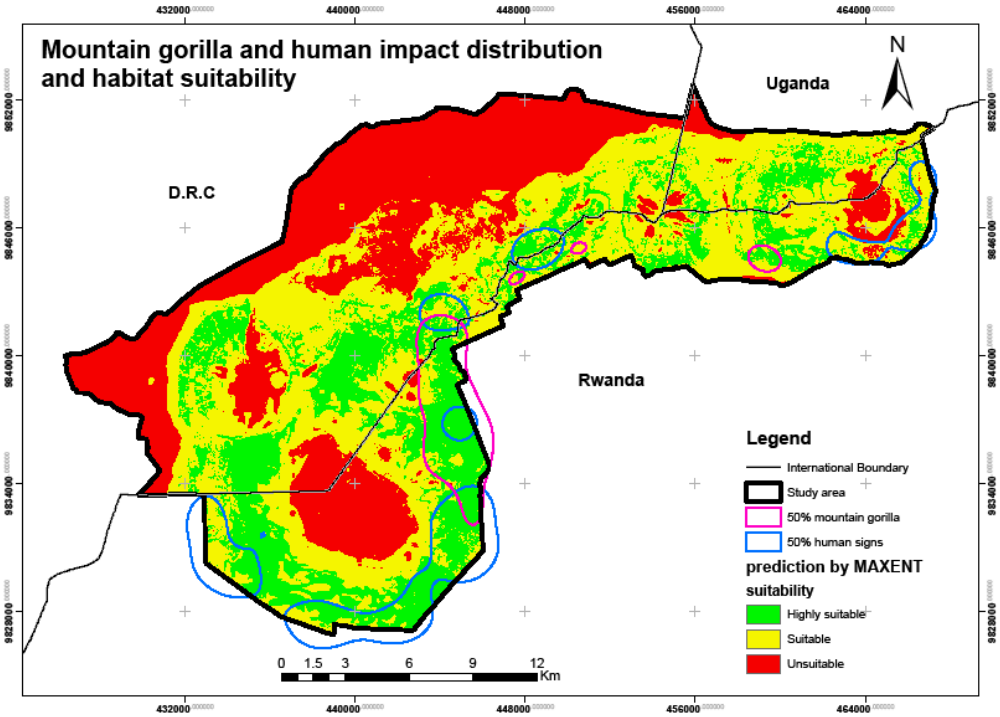

Figure 3-9: Mountain gorilla and human impact core areas (2006) overlaid on Mountain gorilla habitat suitability

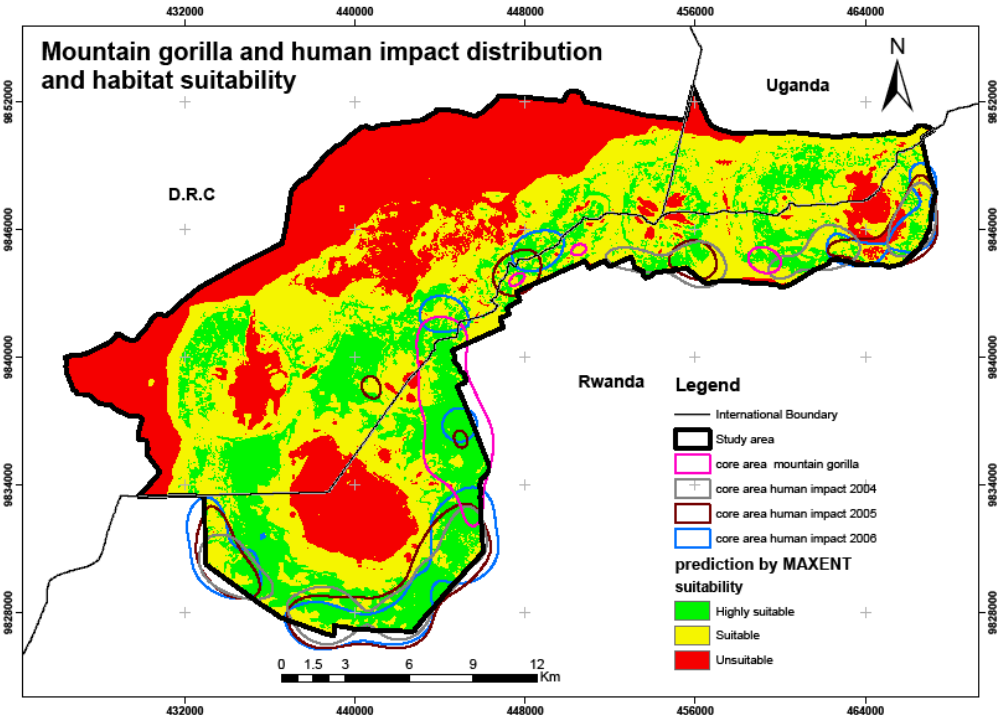

Figure 3-10: Mountain gorilla and human impact (2004 and 2005) core areas overlaid on Mountain gorilla habitat suitability

The negative correlation between human signs and gorillas should be seen with care as some of them are carried out together. For example, positive correlations are found between snares and beehives (r = 0.9), snares and water collectors (r = 0.9), water collectors and beehives (r = 0.9). These positive correlations between some of human signs in the park would mean that some areas are more susceptible to have more human impact than others. In the next section, we investigate the vulnerability of the park to human impact.

3.2.2. Vulnerability analysis

The accessibility model gives a map representing travel time from villages to a certain point in the park. It can be seen from figure 3-11 that areas near the park boundary are more susceptible to vulnerability than the interiors but with different degrees because of the resistance factors applied to the accessibility. The higher vulnerability areas are believed to have more impact on the park, therefore candidate to more pressure from outside the park.

Human signs and the habitat suitability map were crossed with the vulnerability map. 26 % of the suitable habitats (green and yellow colours on the suitability map) fall into the vulnerable areas to high vulnerable areas (reddish colour on the vulnerability map) and are affected by 86 % of human signs encountered in the park.

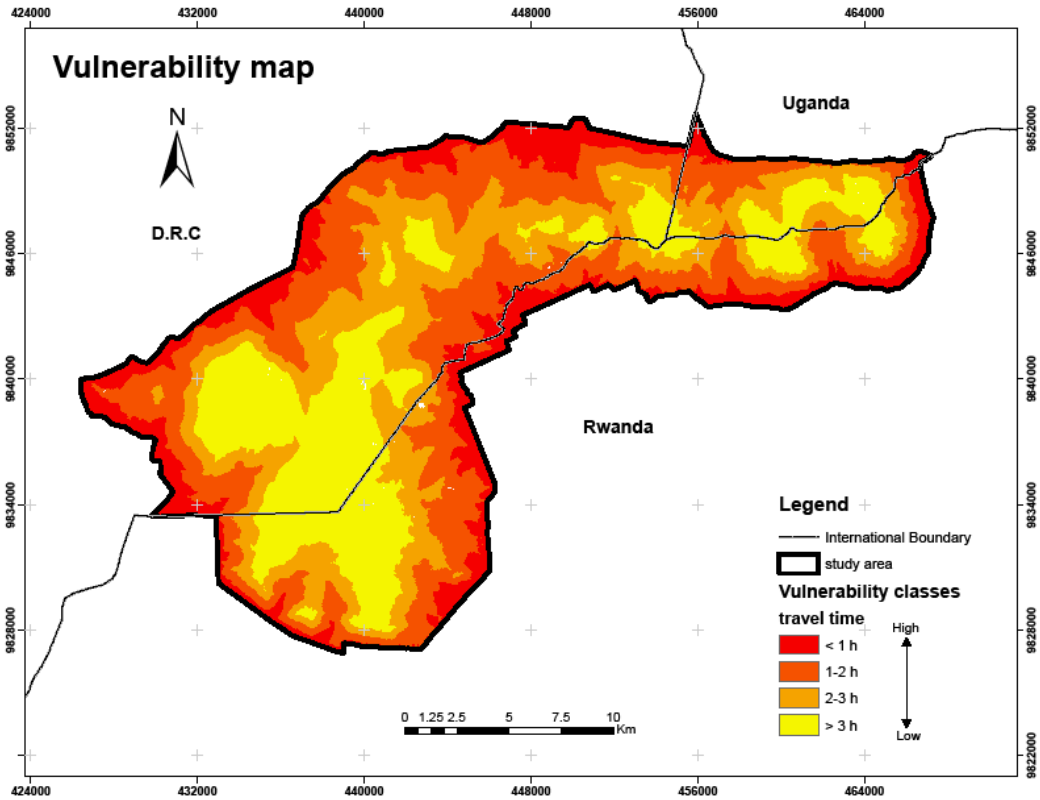

Figure 3-11: Vulnerability map zones of the Virunga Volcanoes Mountains
Gradually from red to yellow colours showing high to low vulnerability

4. Discussion

4.1. Comparison of different modelling algorithms

Both algorithms performed significantly better than random, and MaxEnt achieved better results than GARP. ROC analysis, the threshold independent method used to evaluate both models, showed significantly better than random performance for both algorithms. The area under the ROC curve (AUC) was higher for MaxEnt. The values of AUC (0.76 – 0.89) obtained are very good given the fact that this is modelling with presence-only data (Phillips et al., 2006).

The higher AUC obtained for MaxEnt could be explained by its advantage of distinguishing between the suitable areas with a marginally strong prediction versus the suitable areas with increasingly stronger predictions (Phillips et al., 2006). This is observable on the ROC curve plots where the difference between both models is noticeable especially at the left in the lower part of the plot.

The difference of both algorithms lies also in their output format. While MaxEnt gives a continuous prediction from 0 to 100 with a cumulative increase, GARP gives a binary prediction and the sum of the ten best subsets models gives a continuous prediction from 0 to 10 with an increase in increments of 1. consequently, MaxEnt predicts extremely low probabilities compared to GARP as also found out by Phillips et al. (2006). This is the case in the central part of the study area in the Democratic Republic of Congo where GARP failed to predict suitability conditions.

4.2. Habitat suitability and environmental variables

Animals should spend most of their time in more suitable areas of their home range which reflects the environmental feature selection in their geographical region (Liu, 2001; Vedder, 1984; Watts, 1991). This study found that elevation, slope and vegetation type were the main environmental variables determining the mountain gorilla habitat suitability. Statistical analysis to reduce environmental variables is important to justify the selection from nine to four environmental variables used in the model. The method used to reduce the variables is commonly used and have been used in other habitat suitability studies (Bonn and Schröder, 2001; Hernandez et al., 2006). However, more robust method exist such as Variance Inflation Factor (VIF) (Brauner and Shacham, 1998).

Elevation was chosen as proxy for climatic variables after several tests of model run scenarios. In all scenarios, elevation had the highest contribution to the model compared to the climatic

variables and the latter were static and had the same gain. When climatic variables were removed the accuracy of the model didn't change however the elevation contribution increased holding information of the climatic variables removed.

The high elevations in the study area are highly correlated with lower temperature and high quantities of rainfall. Such areas have been reported to be avoided by mountain gorillas because they increase their susceptibility to respiratory infections causing seasonal variation in mortality (Watts, 1998c). Elevation had the highest gain in the model when it was used in isolation and decreased most the gain when omitted and contribute 58%. The high contribution of elevation to the model predictions should be interpreted with caution because of undetected collinearity with vegetation types. Weber (1987) stated that vegetation in the Virunga is first characterised by altitude and micro-climates. Figure 3-2 shows that some of vegetation types follow an altitudinal gradient (vegetation belts) such as bamboo and *Hagenia-Hypericum* forests but that pattern is not observed for the whole study area implying other factors playing a role in the vegetation distribution.

The vegetation types in the experimental model caused the decrease in the gain most when omitted, having information not present in the other variables and rank second, after elevation, when omitted in the model. The investigation of vegetation types use by Mountain gorillas in relation to their availability when considering all vegetation types revealed that vegetation type selection is not due to chance ($\chi^2 = 1833.11$, d.f. = 8, $p < 0.001$). This is in accordance with Watts (1991) who found that the vegetation type area and total occupancy time of a group of mountain gorilla were significantly related. The vegetation type most selected was the *Hagenia-Hypericum* forest (40%), followed by Bamboo forest (20%) and herbaceous (14%). These vegetation types which explain 75% of the distribution of mountain gorillas fall within the altitudinal range which is modelled as suitable. The high elevation which corresponds to vegetation types which are not or less selected by Mountain gorillas fall in less suitable or unsuitable areas. This is the case for the alpine meadow and brush ridge. It is reported that the foods unique to high altitude zones contributed little to the gorillas' diet (Fossey, 1977; McNeilage, 1995). Some others were moderately selected such as *Mimulopsis*, *Neobutonia* forest and mixed forest.

The vegetation type selection is explained by the quantity and quality of food availability within them as the mountain gorilla distribution is influenced by the distribution and abundance of high food quality (Vedder, 1984; Watts, 1998a). Vedder (1984) and Watts (1991) reported that the frequency and length of visits to a given area and the overall use of areas were positively related to availability of high quality food. The *Hagenia-Hypericum* forest forms an open canopy and allows the establishment of a rich understory biomass which contains more protein food for mountain gorillas including the most selected food such as *Gallium*, thistle, celery, *Vernonia*, etc (Fossey, 1977; Vedder, 1984; Weber, 1983). The Bamboo forest is commonly occupied by gorillas at low densities or during the bamboo shoots

period. these bamboo shoots are the most favoured food for mountain gorillas wherever they fall into their home range (Fossey, 1977; Vedder, 1984; Watts, 1998b). Fossey (1977) reported that they can form 90% of the diet of a group at the peak of the shooting season. However, in areas where there is no bamboo, such patterns are not observed. Watts (1998c) also report that the bamboo can skip shoots production periods . We did not include seasonality in this study due to the fact that with regard to the overall distribution of mountain gorillas, seasonality is less pronounced and bamboo forest which determines the seasonal ranging is not evenly present in the whole study area.

The big proportion of the highly suitable habitats in the results part is found in the *Hagenia-Hypericum* forest concentrated in western part of the study area between and on the gentle slopes of the volcanoes Karisimbi, Bisoke and Mikeno, the area which is reported to host high densities of mountain gorillas (Gray et al., 2005; Weber, 1983) and in the herbaceous on the slopes of Bisoke and Sabyinyo. Bamboo forest on the gentle slopes of the Karisimbi, on the foot of Sabyinyo and around Gahinga ranges from highly suitable to suitable habitats and areas which are categorized as unsuitable comprises the volcanoes summits vegetation and the big ravines on the Sabyinyo volcano. These unsuitable areas correlate also with areas with steeper slopes which are reported to be poorly vegetated and/or nutritionally deficient (Weber, 1983). Though, the habitat suitability classes are spread out on all slope classes from flat through gentle to steeper slopes. Topography is also cited to influence visit duration in a vegetation type (Watts, 1991).

Groves et al (1985) report that gorillas prefer nesting on flat terrain but also on slopes with thermal benefit orientation. The solar radiation with topography shading used in the model instead of slope aspect, as cited by Kumar and Skidmore (2000) that, in mountainous area, topographic shading (because it accounts for energy balance) is more important than surface orientation, has a positive relation with habitat suitability. The solar radiation in our study area increases with altitude but also takes into account slope and slope aspect in their calculation as the latter influence on the solar radiation received at a certain point which changes its distribution in the altitudinal ranges (appendix 7-1). The high values of solar radiation in high altitudes are associated with decreases in air density and the amount of dust and water vapour (Gale, 2004). However, solar radiation calculation should include the cloud cover as the latter reduces the energy reaching an area; here the calculation was made using values for a clear sky (ESRI, 2006). The solar radiation contribute to The suitable conditions of gorillas by two main reasons: the thermal effect for nesting places (Groves and Pi, 1985) and the development of heliophile plants (e.g. bamboo) (Bitariho and Mosango, 2005) and understory biomass (food for gorillas) in open canopies of *Hagenia-Hypericum* forest (Weber, 1983).

It would also have been better to incorporate soils types and geological substrate in the model as underlying determinant of food quality of the vegetation types, therefore, such data were lacking. We assumed that soil types are more or less the same given the fact that the study area

is lying on volcanic lava (Jost, 1987). Also it should be added that mountain gorilla presence data were obtained from the Rwandan side of the study area with relatively in higher altitudes compared to the study area in the Democratic Republic of Congo. Some areas in these low altitudes in D.R.C could have been poorly correctly predicted. However, the distribution patterns of mountain gorillas observed in 1976 and 1978 censuses by Weber et al. (1983) and by Gray et al. (2005) in 2003 census also showed that these areas of low altitudes are not or less used by mountain gorillas.

4.3. Habitat suitability and human impact

The environmental distribution of hazards can influence foraging macro-strategy of animals (Watts, 1991). The negative correlation between gorilla density probability distributions and most of the location of human impact found in this study as also found by Gray et al (2005) during the 2003 census in the census sectors could attest that human impact have an negative effect on gorilla distribution. Some reasons could be for example the vegetation degradation through bamboo/wood collection which reduces or remove the quality of food preferred by gorillas; snares in which gorillas get caught in or noise from people. The human impact could have three major implications (Gray et al., 2005): direct kills reducing the population, stress increasing mortality or decreasing reproductive rates and shifting home ranges.

These three implications are at the origin of a dramatic decline of gorilla population from 450 to about 250 individuals during the 1960s and 1970s as result of large scale suitable habitats loss, direct poaching of gorillas and decreased reproductive rates resulting from the stress put on affected gorillas (Weber, 1983). By 1989, the population had increased to about 324 individuals with an increase of 3% annual growth rate due to conservation effort, especially anti-poaching patrols initiated in the 1980s (Weber, 1983) and by 2003 the population was 380 individuals with an increase of 1.15 % annual growth rate (Gray et al., 2005). The carrying capacity of the Virunga Volcanoes Mountains is estimated to 650 individuals (McNeilage, 1995; Weber, 1983). Under natural conditions i.e. in the case of the absence of human interference, higher growth rate could be achieved and the carrying capacity can be reached (Werikhe et al., 1998).

However, the region around the Virunga Volcanoes Mountains has high population densities with a growth rate of about 3 %. Under these conditions it is expected that the population would double in 30 years (Werikhe et al., 1998). More people would mean less resource available outside the park and more pressure to the park, thus, more human impact inside the park. The human population is already associated with the large loss of the suitable habitats during the 1960s and 1970s. This type of activity seems to have been stopped and the park boundary stabilized; however, different human signs conducted in the park have different degrees of negative impacts on gorillas.

The degradation of the habitat suitability through vegetation removal for different purposes (bamboo, wood…) could have a serious negative effect. This degradation gradually renders parts of the habitat unsuitable and could fragment the habitat suitability into multiple different patches. The vegetation degradation could be verified through change detection analysis. Initially planned in this study but due to the fact that degradation happens in very small scale in a forest area to be able to detect in the image (30 by 30 m) were dropped. However, with the newly available IKONOS images of the region, such analysis could be done and provide some evidence of the impact of vegetation degradation on habitat suitability. In the same way, high food quality could be also investigated using hyperspectral imagery.

Not only vegetation degradation has serious negative effects but also, with different weight, snares and noise from people carrying activities in the park. It is reported that over the last fifteen years, the number of gorillas killed is relatively small compared to the potential growth that gorilla population could have shown (Gray et al., 2005). However noise, from people and sometimes scaring the gorilla groups, could have more impact as the gorillas react by fleeing or shifting the home ranges away from people leading to increased stress in gorilla population causing increased mortality or decreased reproductive rates. Watts (1991) reports a group of gorillas not utilizing for at least 5 months its base area of high food quality after poachers attacked the group. Our results shows that mountain gorillas avoid high density of human impacts, although located in the suitable habitats. The core areas of mountain gorillas and human impacts areas hardly overlap (figure 3-9, figure 3-10). Gray et al. (2005) also indicated that in 2003 census gorillas were found in areas with low human impacts.

The investigation of previous years 2004 and 2005 showed also the same pattern of human impacts concentrated in the same areas and avoided by gorillas. This leads to investigate areas which are likely susceptible to have more human impact in the park, thus more vulnerable. The frequency and intensity of human activities on wildlife are determined of how close people are settled (de Leeuw et al., 2002).

Thus, as should be expected, highly vulnerable and vulnerable areas are associated with more human impacts (respectively 63.7 % and 26.1 %) inside the park. The overlap of suitable areas with vulnerable areas also show high human impact associated with these areas. 86% of human impacts are observed in the spatial overlap (26%) of suitable habitats with highly vulnerable to vulnerable areas. However the vulnerability analysis could also have taken into account the motivation of people to enter the park based on the resource needs (shortage). This leads to different vulnerabilities for different resources. It is assumed that the motivation is the same around the park as the majority lives on small scale subsistence agriculture with more than half under the poverty line (Lanjouw et al., 2001).

The spatial overlap of vulnerable areas with the gorilla suitable habitats poses a great concern with regard to gorilla population and habitat viability in case e.g. of a disease outbreak as both

use the same areas. Diseases are great threats to wildlife especially for endangered species and closely related species like humans and gorillas (Werikhe et al., 1998). Some diseases are already known to have been transmitted from people to mountain gorillas such as scabies, measles and intestinal parasites(Kalema-Zikusoka et al., 2002; Sleeman et al., 2000; Werikhe et al., 1998) others from primates to humans such as Ebola, from chimpanzee (Pan troglodytes) (Werikhe et al., 1998).

Disease analysis simulations conducted for mountain gorillas for different types of diseases (Influenza- like disease; Severe, but not pandemic, viral disease and hypothetical viral disease with chronic cyclicity) showed that gorillas face a great threat with a considerable risk of extinction (Werikhe et al., 1998). In western lowland gorillas (*Gorilla gorilla gorilla*) Bermejo et al. (2006) report an outbreak of Ebola in killing about 5,000 gorillas in 2002 and 2003. Not only in the case of the diseases illegal human impact is concerned but also legal human activities (researchers, rangers, tourists, etc.) (Werikhe et al., 1998; Woodford et al., 2002).

It is obvious that human impact inside the park affects mountain gorilla habitat suitability and that spatial overlap between gorilla habitat suitability and vulnerability areas increases the threat to them. In addition, with rising human population densities, the extent of human-gorilla interaction increases, therefore, the threat is also believed to be noticeably higher.

4.4. Management implications

This study proved the relationship between the mountain gorillas and human population and the implications that this relationship is subject to. The interactions of mountain gorilla habitat suitability with the vulnerability areas and human impact arouse some attention to the effective conservation of mountain gorillas both inside and outside the park.

Inside the park conservation measures should focus on the preservation of the habitat suitability by:

- Regular monitoring of the habitat suitability: this can be possible using Geographic Information Systems and Remote Sensing as information on the habitat quantity and quality change can be analyzed and easily updatable on the entire area within relatively low cost and short time.
- Increased anti-poaching patrols: the interaction between the habitat suitability and vulnerability areas are identified. Patrols could be oriented in these areas for better protection.

Outside the park, the conservation measures should focus on:

- Decreasing the vulnerability of the park by reducing the accessibility. This could be done by applying a buffer zone to the park which would contain the products which

are collected inside the park or with an economic value to increase people' economic situation. However, the feasibility of these measures is rather difficult given the fact that the area is already heavily populated and the land available is not sufficient to people. The park has been heavily reduced so that there is no option of giving the buffer zone from the park. The only option would be to buy land from people. Another option to reduce the accessibility could be to apply a fence to the park. Again dilemmas for this option rise. On one hand, it is beneficial for the park if the fence is well monitored and maintained because it reduces significantly the accessibility, mark clearly the park boundary from the people's fields and stop cropraiding from buffalos but on the other hand people would feel rather excluded from "their" park and would be more hostile vis-à-vis the park and the cost involved in the fencing.

- Decreasing the motivation of people to enter the park: Improving the economic situation of people as it was found that as the economical security of the population improves; the direct exploitation of the resources of the park decrease (Werikhe et al., 1998). This measure already in place by the policy of revenue sharing from tourism activities. However, vulnerabilities analyses for different resources collected in the park are needed. These studies would enable to spatially locate what interventions needed based on the resource shortage of the areas e.g. by identifying which areas (e.g. cells) suffer from water shortage or wood shortage… The underlying idea being that areas with a surplus of the resource will have less motivation to enter the park for that resource.
- Reducing disease risks: providing health care to people around the park starting with areas where interactions with the gorillas are higher.
- Improved education: education plays a big role in changing people's values and behavior. Recognition of non-economic values of the park, family planning, other revenue alternatives than farming, emigration… are some of the benefits of education in reducing vulnerability to the park.

However, all the above mentioned conservation measures could be more effective considering the whole Virunga Volcanoes Mountains, the transboundary collaboration being a key to in the conservation success. Although, the three parks have different managements and laws governing them, transboundary collaboration between Congo, Rwanda and Uganda is acknowledged to have an impact on the increase of gorillas registered and on reduction of the decline of elephants during the civil war during1990s (Plumptre et al., 2007). However, more should be done to reinforce this collaboration (Plumptre et al., 2007) as mountain gorilla do not have borders in their ecosystem. The international recognition should also consider the whole area as one park not as three different entities e.g. Parc National des Virunga in Congo is recognized as a World Heritage Site while the other two segments are not.

5. Conclusion

This study explored the relationship between the mountain gorilla habitat suitability and how human activities impact on this habitat.

The main findings can be summarized as follows:

1. Elevation was the main environmental variable associated with mountain gorillas' habitat suitability. Incoming solar radiation, vegetation types and slope have also an important effect on the habitat suitability.
2. MaxEnt was the best model in predicting mountain gorilla habitat suitability and produced good predictive map of gorilla suitable areas in the Virunga Volcanoes Mountains.
3. Negative correlation was found between gorilla habitat utilization and human impacts and spatially gorillas avoiding concentration of human impact areas.
4. Vulnerability analysis showed areas of high human impact affecting the mountain gorillas' habitat suitability.
5. We discussed the threat implications linked with interaction of vulnerable areas, human activities and gorilla population and habitat viability and we discussed also management implications in addressing these issues.

In summary this study in conservation application gives evidence that information resulting from studying the relationship between mountain gorillas and human impact can be integrated into park management and leads to better conservation activities.

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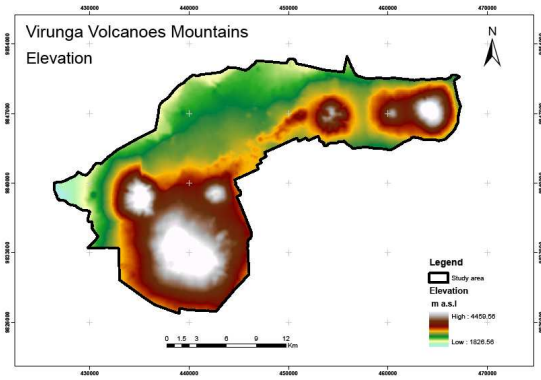
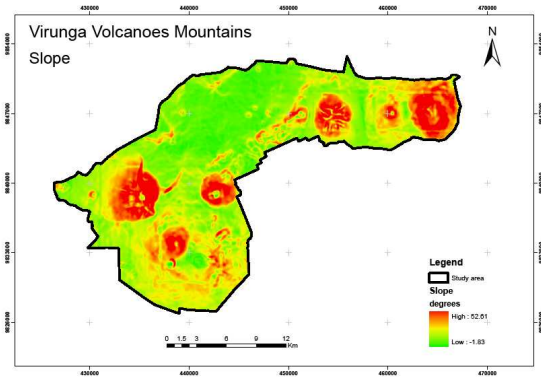
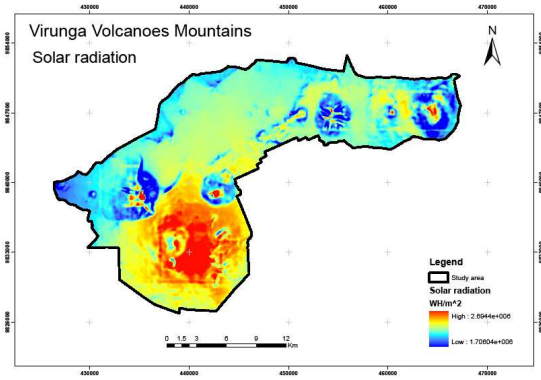
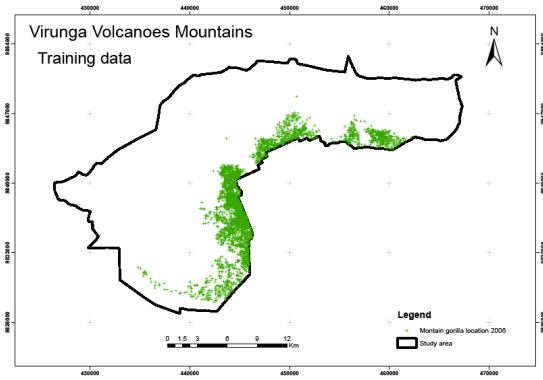
7. Appendices

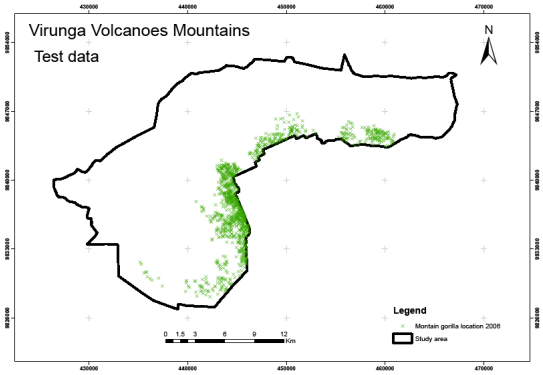
7.1. Environmental variables and gorilla presence training and test dataset maps



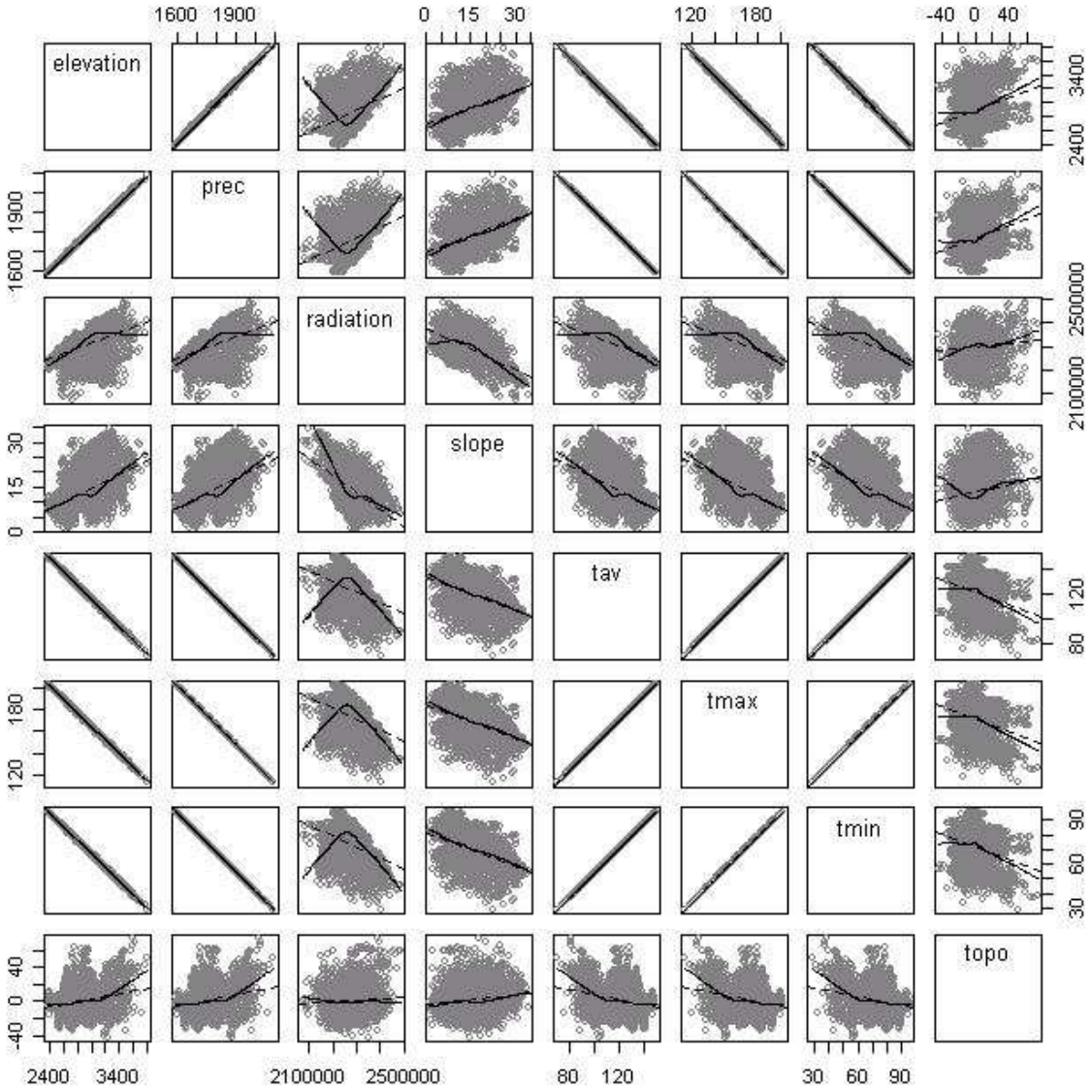








7.2. Scatterplots of continuous environmental variables

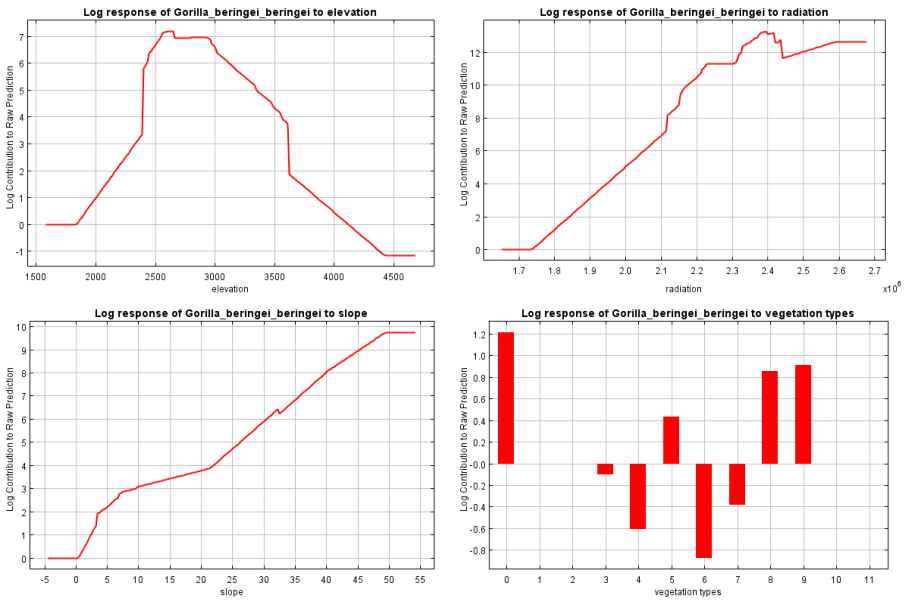


7.3. Linear regression of continuous environmental variables

Variable1	Variable2	R^2	p-value	Variable1	Variable2	R^2	p-value
elevation	slope	0.191	9.1E-211	topo	prec	0.072	2.79E-76
	topo	0.065	1.15E-68		tmin	0.0729	2.79E-76
	prec	0.998	<0.0001		tmax	0.0729	2.79E-76
	tmin	0.998	<0.0001		tav	0.0729	2.79E-76
	tmax	0.998	<0.0001		Radiation	0.00735	5.008e-09
	tav	0.998	<0.0001				
	Radiation	0.18	< 2.2e-16	prec	tmin	1	<0.0001
slope	topo	0.023	1.34E-25		tmax	1	<0.0001
	prec	0.191	8.5E-211		tav	1	<0.0001
	tmin	0.191	8.5E-211		Radiation	0.18	<2e-16
	tmax	0.191	8.5E-211				
	tav	0.191	8.5E-211	tmax	tav	1	<0.0001
	Radiation	0.34	< 2.2e-16		Radiation	0.18	< 2.2e-16
tmin	tmax	1	<0.0001				
	tann	1	<0.0001	tav	Radiation	0.18	< 2.2e-16
	Radiation	0.18	< 2.2e-16				

7.4. Response curves of MaxEnt model

These curves show how each environmental variable affects the MaxEnt prediction.



7.5. Accessibility model construction tables

Travelling speed per road types

Road type	**Travelling speed**
Main road	6
Secondary roads	6
Tracks	4
Paths	4
Trails (inside the park)	3

Slope steepness and slope correction factor

Slope steepness	Slope correction
0 – 5%	1
5 – 10%	0.96
10 – 20%	0.82
20 – 30%	0.65
30 – 45%	0.50
45 – 65%	0.41
65 – higher	0.29

Travelling speed per land cover type

Land cover class	**Expected travelling speed**
Bamboo forest	0.5
Hagenia-Hypericum forest	0.8
Brush ridge	2
Mixed forest	0.8
Neobutonia forest	0.8
Alpine meadow	2
Meadow/savannah	2
Herbaceous	2
Mimulopsis	2
Water	0
Agriculture fields	3
Forest plantations	1
Bare/settlements	3