# Masters Program in Geospatial Technologies

SPATIAL POINT PATTERN ANALYSIS OF GORILLA NEST SITES IN THE KAGWENE SANCTUARY, CAMEROON.

*Towards understanding the nesting behaviour of a critically endangered subspecies.*

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Dissertation submitted in partial fulfilment of the requirements for the Degree of *Master of Science in Geospatial Technologies*

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SPATIAL POINT PATTERN ANALYSIS OF GORILLA NEST SITE DISTRIBUTION IN THE KAGWENE SANCTUARY, CAMEROON.

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## Dedication

To the inspiring memories of Dr Ymke Warren for her impeccable efforts in Cross River Gorilla conservation.

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# SPATIAL POINT PATTERN ANALYSIS OF GORILLA NEST SITE DISTRIBUTION IN THE KAGWENE SANCTUARY, CAMEROON

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**ABSTRACT**

Gorilla nest site data from the Kagwene sanctuary, Cameroon were analyzed to foster an understanding of the nesting behavior of Cross River Gorillas. The main objective of the study was to verify the pattern of nest site distribution in the sanctuary, the influence of environmental covariates and possible interaction between nest sites and between nest sites of two gorilla groups – the Major and Minor groups. Spatial point pattern analysis methods were implemented in the R software environment for this purpose. Overall, we sought to fit models that could best estimate an intensity function for nest site distribution in the sanctuary. Resulting models revealed that nest site distribution does not conform to a Poisson process, and that the data can be better described by a combination of environmental factors and interaction between nest sites. Univariate models fitted to different nest site categories proved to be more useful than bivariate models in defining intensity functions for nest site distribution. The final model category chosen for the data therefore constituted a combination of the effect of covariates and higher-order interaction between nest sites. This set of models, chosen through their AIC values, showed that nest site distribution in the sanctuary exhibits characteristics of attraction so that clustered patterns are observed. Gorillas tend to create hotspots for nest site location, with southern parts of the sanctuary proving to be very much avoided. Intensity tends to increase with increasing distance to the centre of the sanctuary. Coefficients obtained from the models also showed that gorillas prefer constructing nests close to transition vegetation, on steep slopes and generally on east-facing slopes. In the dry season however, colonizing forests exert a greater attraction on nest sites, which can be attributed to the fact that transition zones experience such edge effects as bushfires, and plants that provide food (such as Zingiberaceae) do not bear fruit in this season. These can be assumed to be specific habitat requirements of this subspecies of gorillas. Also, intensity drops with increasing elevation. Interaction parameters obtained from the bivariate models also suggested that there is attraction between nest sites of the Major (sites with more than 6 nests) and the Minor groups. This analysis is the first of its kind for this subspecies, and we recommend that further models can be fitted to include a wider range of covariates (both anthropogenic and natural) as they may be available to expand the scope of the models.

## KEYWORDS

Conservation

Cross River Gorilla (*Gorilla gorilla diehli*)

Kagwene Gorilla sanctuary

Nest site distribution

`R`

Spatial Point Pattern analysis

Spatial distribution pattern

`spatstat`

# ACRONYMS

AIC – Akaike's Information Criterion

ASTER – Advanced Spaceborne Thermal Emission and Reflection

CR Gorilla – Cross River Gorilla

CSR – Complete Spatial Randomness

CSRI – Complete Spatial Randomness and Independence

DEM – Digital Elevation Model

GDEM – Global Digital Elevation Model

GPS – Global Positioning System

HPP – Homogeneous Poisson Process

HMPP – Homogeneous Multi-type Poisson Process

iid – Independent and Identically Distributed.

IMPP – Inhomogeneous Multi-type Poisson Process

IPP – Inhomogeneous Poisson Process

IUCN – International Union for Conservation of Nature

KGS – Kagwene Gorilla Sanctuary

MPLE – Maximum Pseudolikelihood Estimation

PPP – Point Pattern Process

WCS – Wildlife Conservation Society

WCS-TMLP – Wildlife Conservation Society- Takamanda Mone Landscape Project

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# CHAPTER 1: INTRODUCTION

## 1.1 Study background.

One important requirement to the success of wildlife conservation is the understanding of the behavior (etho-ecology) of the wildlife species especially with reference to its environment. Obtaining an understanding of animal behavior through field studies is important for designing captive breeding programs for endangered species and in helping to conserve endangered wild populations. Without such knowledge, conservation programs may result in drastic waste of resources, money and time. For centuries, conservation scientists have sought this understanding and continue to do so as new species of animals get discovered or as species get split into subspecies. About a hundred years ago (1904), eight skulls of gorillas found in the Cross River region of Nigeria and Cameroon were examined by the German taxonomist Matschie, and this cranial examination revealed distinctions between the Cross River Gorilla (CR gorilla) and other Western Lowland gorillas. He proposed that this group of gorillas was distinct enough to constitute a separate gorilla species, the *Gorilla diehli* (Sarmiento and Oates 1999). Other researchers disagreed with Matschie, asserting that the CR Gorilla was actually a subspecies of the Western Lowland gorillas, and should be known as the *Gorilla gorilla diehli* (as they are known today). For some years later, gorilla surveys died down in this region and the subspecies was thought to be lost until the 1980s when gorilla groups were rediscovered in the Mbe Mountains (Sarmiento and Oates, 1999), and further surveys revealed the existence of gorillas (*Gorilla gorilla diehli*) in different parts along the Cross River region. Today, it appears on the International Union for Conservation of Nature (IUCN)'s Redlist as the most critically endangered primate (IUCN 2005).

Since the rediscovery of this subspecies, research has been geared towards understanding their behavior for effective conservation practices. Research on gorilla groups along the landscape reveals that they actually portray different behavioral characteristics in different habitats (Sunderland-Groves 2008). Sunderland-Groves actually describes them as 'adaptable' in terms of feeding behavior because they tend to have different diet choices in different localities. It is usually therefore necessary to study each group of gorillas discovered, since it may be misleading applying results of studies from one group to other groups. A myriad of studies have been carried out towards understanding the ecological behavior of Western Lowland gorillas (Brugiere and Sakom 2001; Casimir 1979; Goldsmith 2003; Mehlman and Doran 2002; Remis 1993; Tutin *et al.* 1995) but very few have sought the investigation of the behavior of CR gorillas (McFarland 2007; Sunderland-Groves 2008; Sunderland-Groves *et al.* 2009; De Vere *et al.* 2010). Most of the studies on CR Gorillas have been based on the effect of anthropogenic activities on nesting behavior (De Vere *et al.* 2010) and on seasonal distribution patterns (Sunderland-Groves *et al.* 2009) using ecological assessment and classical statistical methods to analyze nest site data. However, none of these studies has been geared towards spatial statistical methods, or on modeling and predicting nest site distribution. We believe that spatial point pattern analysis of nest site distribution will provide valuable insights to the effect of environmental variables on nest site distribution, the effect of interaction between nest site locations and on interaction between different gorilla groups. This thesis follows this line of research by utilizing the power of computational spatial point pattern statistical methods to mine into the nesting behavior of the rarest ape currently known to man, the Cross River (CR) Gorilla.

### 1.2 Objectives of study and research questions.

The overall objective of this study is to analyze the spatial distribution of CR gorilla nest sites in the Kagwene sanctuary of Cameroon utilizing spatial point pattern modeling methodology. The study was intended to characterize nest site distribution in the sanctuary, and to fit models that can estimate an intensity function for nest site distribution.

The study set out to answer the following specific questions:

- Are gorilla nest sites randomly distributed in the sanctuary or are there any ecological processes going on that cause them to either cluster or disperse? It was our goal to verify if nest site distribution is uniform in the sanctuary, and conforms to a random rather than a non-stationary process. If nest site distribution is not random, what other pattern does it exhibit?

- How does each of the selected covariates affect nest site selection by CR gorillas in the sanctuary? This study was designed to verify whether or not the selected variables affect nest site distribution in the sanctuary and if they did, how?
- Can nest site distribution be explained solely by environmental variables or there exists some higher-order interaction between points? If nest site distribution was not in conformity to an inhomogeneous Poisson Process (IPP), then what is the level of higher-order interaction that exists between nest sites?
- What is the relationship between nest sites of the Major gorilla group and those of the Minor group in terms of spatial location? It was the aim of this study to verify if, and to what level there was a relationship between nest site location of the Major group and the Minor group. Do they repel or attract each other, or there simply is no higher-order relationship between them?

### 1.3 Structure of the thesis

This thesis is organized into five chapters, which follow a chronological flow of ideas as follows:

*Chapter 1- Introduction*.

This chapter presents a background to the study, objectives and structure of this thesis.

*Chapter 2- Gorilla distribution and conservation and application of spatial point pattern analysis.*

This chapter reviews literature related to the distribution of gorillas in general, their conservation status and ecological behavior.

*Chapter 3- Materials and Methods.*

Here, we present the software tools used for the thesis, sources and description of data and analysis methods implemented in the study.

*Chapter 4- Results of analysis.*

In this chapter, we present the results obtained from statistical analysis of the data.

*Chapter 5- Discussion, future research and conclusion.*

We present discussion on the results of analysis in this chapter. Recommendations on the directions for future research, and general conclusions are also presented here.

# CHAPTER 2: GORILLA CONSERVATION AND SPATIAL POINT PROCESS MODELLING.

## 2.1 Gorilla subspecies and conservation status.

The largest of living primates - gorillas are divided into two species: *Gorilla gorilla* (Western gorilla) and *Gorilla beringei* (Eastern gorilla). These are further divided into four subspecies; *Gorilla gorilla gorilla* (the Western lowland gorilla), *Gorilla gorilla diehli* (the Cross River gorilla), *Gorilla beringei graueri* (the eastern lowland or Grauer's gorilla) and *Gorilla beringei beringei* (the Mountain gorilla) (Bergl 2006). All these subspecies of gorilla are endangered (IUCN 2005) as a result of such anthropogenic and natural factors as hunting, habitat loss, and diseases (especially the Ebola virus) but the *G. g. diehli* is the most critically endangered of them all, and of all apes put together (Mittermeier *et al.* 2006).

Cross River gorillas number hardly more than 300 in the wild today (Bergl 2006; Sunderland-Groves 2008; Oates *et al.* 2007; Sunderland-Groves *et al.* 2003) and this population is scattered over about eleven habitats in Nigeria (Afi mountains, Mbe Mountains, Boshi Extension) and Cameroon (Takamanda South, Takamanda East, Takamanda North, Kagwene Mountains, Bechati-Lebialem) and along the Cameroon-Nigeria border (Okwangwo-Takamanda) (Bergl 2006).

## 2.2 Geographical distribution of gorillas.

All four gorilla subspecies are found exclusively in the African continent. They all range in forest regions (Figure 1). Gorillas range in both highland and lowland regions. In the east of Africa, the *Gorilla beringei beringei* is a highland subspecies (commonly referred to as Mountain gorillas) while the *Gorilla beringei graueri* is a lowland species (commonly called the Eastern lowland gorilla). To the west/central Africa are gorillas of the species *Gorilla gorilla*. Of the two subspecies that make up this group, the *Gorilla gorilla gorilla* is a lowland subspecies (Western lowland gorillas) while the *Gorilla gorilla diehli* (Cross River Gorilla) is commonly located in hilly and difficult terrains, sometimes measuring over 2000 m in height. Of all four subspecies, the Cross River gorilla (the subspecies for this study) is the most northerly and westerly in extent.

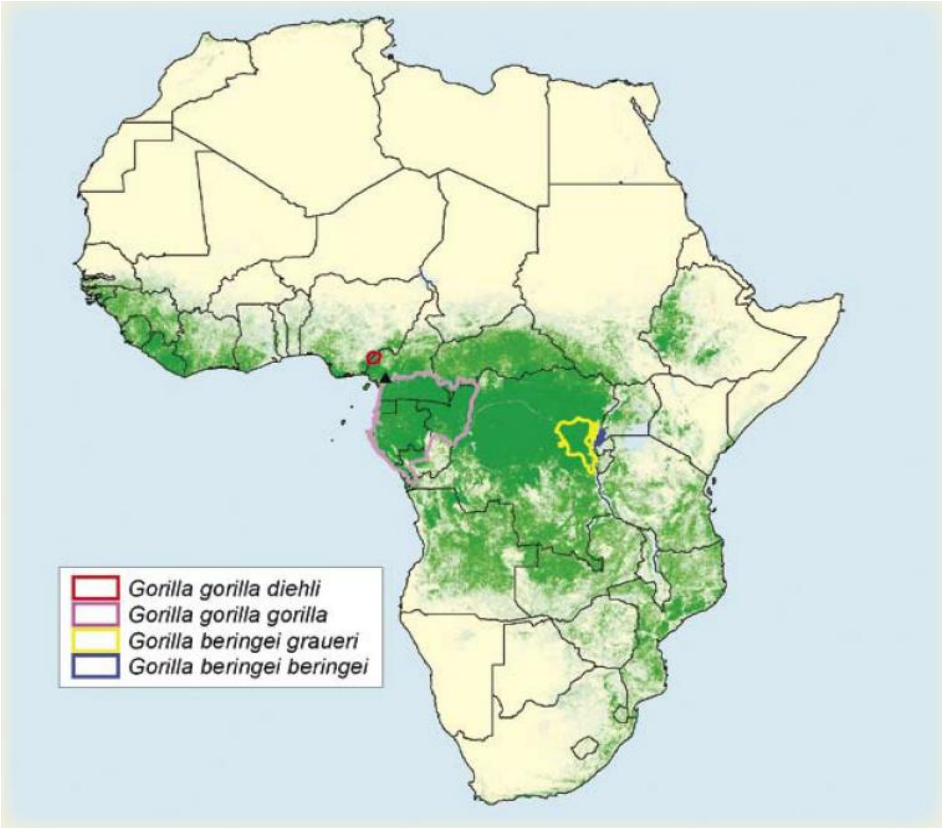



Figure 1: Map of gorilla distribution (taken from Oates *et al* (2007))

### 2.3 Behaviour of the *Gorilla gorilla diehli.*

Gorillas have been described as adaptable in terms of diet because they rely on different food types in different regions (Sunderland-Groves 2008). Like other gorillas, CR Gorillas spend a greater part of their day eating, but differ from other Western gorillas in choice of diet (Oates *et al.* 2007) CRGs feed on herbaceous plants throughout the year, and a variety of fruits when available. In the Kagwene Sanctuary, they feed on a variety of fruits such as figs, *Psychotria sp*. and 'aga', and herbs, such as, Zingiberaceae (*Afframomum* sp), *Amorphophallus difformis*, Acanthaseae, Commelinaceae (*Commelina cameroonensis*, *Palisota mannii*) (WCS-TMLP long-term records). These food sources constitute a major habitat requirement for the gorillas. Any activity that causes a destruction of these sources therefore is expected to play down on the very existence of CRGs in this locality.

In the Kagwene Sanctuary, the gorillas appear to range as two social groups, the Major (seven to nine in number) and the Minor group (five to seven in number) with overlapping home ranges (WCS-TMLP long-terms records). Each of these social groups is led by a dominant male- the silverback. These groups move about in search of food in the day, and construct sleeping nests almost every night. In the dry season, they construct many nests on the ground while more tree nests are constructed in the rainy season (Sunderland-Groves *et al.* 2009). Each member of the group, in most cases, sleeps in one nest so that it is possible to know the number of gorillas at each nest site from the number of nests constructed. Exceptions are in cases where there is a juvenile in the group, and in that case may share a nest with an adult gorilla. Nest heights in Kagwene measure up to about 35m (Sunderland-Groves 2008). Studies on the nesting of CRGs in Makone, Obonyi and Basho have revealed that CRGs construct most of their nests in closed canopy forests and very few under open canopies (Sunderland-Groves 2008). Gorillas in the Kagwene sanctuary are also noted to construct nests on precipitous slope, which is probably attributed to security reasons (Wiseman 2008).

### 2.4 Threats to gorilla conservation.

The conservation of CR gorillas is being undermined by a myriad of human factors in different localities. Human activities carried out in and around gorilla habitats are noted to cause habitat loss and/or modification. Such activities include crop farming, pastoral farming, hunting, deforestation caused by bushfires or extraction of timber and non-timber forest products and the like. These factors have been addressed by so many researchers in different localities where CR gorillas are found (Bergl 2006; IUCN 2005; Mittermeier *et al.* 2006; Neba 2008; Oates *et al.* 2007; Sarmiento and Oates 1999; Sunderland-Groves 2008; Sunderland-Groves *et al.* 2009). Previous studies have also explained the influence of some of these factors on gorilla behavior and existence. However, aside from these human-induced factors, the current study holds that it is equally important to explain the behavior of the gorillas in terms of the physical terrain in which they find themselves. CR gorillas are often found in very difficult-to-access terrain, which usually makes field research an unenviable task. It is therefore worth investigating how much of a threat the natural environment in which they find themselves can be. This was a motivation to this study and the reason why the factors included to the models were mostly natural and not anthropogenic.

### 2.5 Application of Spatial point process modeling.

Spatial point processes are models built for random point patterns in different dimensional spaces (usually 2 or 3-dimensions). It is "...a stochastic process in which we observe the locations of some *events* of interest within a bounded region *A*." (Bivand *et al.* 2007). An event here refers to actual observations of points, while the region *A* is usually considered or termed the *window of observation* (Baddeley 2008; Baddeley and Turner 2006). Spatial point process modeling is a major study within the field of spatial statistics that does not only discover the distributional pattern inherent in a point dataset, but also goes beyond to explain why observed points follow a particular pattern.

This modeling technique is an analogy of regression models in classical (non-spatial) statistics, and can be applied to a wide range of fields including forestry and plant ecology (e.g. explain position of particular tree species in a forest stand), epidemiology (e.g. how and why a particular disease is, or group of diseases are distributed in a settlement), seismology (e.g. distrubution of earthquake epicenters), wildlife ecology (e.g. location of nests or burrows of animals), geography (e.g. what affect settlement location), amongst many others.

The essence of spatial point processes modeling is usually to verify whether or not points in a point pattern are distributed in a random manner. Therefore, in point process modeling, the first and most basic tests are based on the concept of Complete Spatial Randomness (CSR) – where events are assumed to be randomly distributed. Any point pattern modeling basically would end at this stage if points in the pattern are tested to follow a random distribution. A rejection of spatial randomness in distribution is the ground on which further models are built. If a test for CSR proves that the points are clustered or dispersed, then we are often faced with the task of explaining why any of these patterns might exist. Model fitting for a point pattern that is not completely random is done with the aim of obtaining the best model that can best explain the distribution of points in the dataset, that is the best model to provide an intensity function for the data. Point process models are important not only to understand the effect of different factors on point distribution, but also to predict point occurrence for other areas where point distribution is unknown.

In the R statistical software, spatial point pattern models can be fitted with packages such as spatstat (Baddeley and Turner 2005) and SPLANCS (Rowlinson and Diggle 1993). These packages provide extensive functionality for model fitting, simulation and prediction, but it is worth noting that they are still limited in the functions built in and in the volume of data they can handle (the latter is a general R limitation). Before models can be fitted using these packages, other support packages are needed for data preparation and input into R. Together with these complementary packages, spatstat and SPLANCS provide an amazingly powerful environment for point pattern modeling.

## CHAPTER 3: MATERIALS AND METHODS.

This chapter describes the methodology implemented in analyzing gorilla nest site data and modeling. It presents the study area, sources of data and tools used to analyze the data.

### 3.1 The study area.

The Kagwene Gorilla Sanctuary (06º05'-06º08'N: 09º42-09º48'E, KGS, Figure 2) is located along the North West-South West Regional boundary of Cameroon and covers an area of 19.44 km². It is one of over 11 habitats where CR gorilla populations are said to exist. The Kagwene Mountains are of the Western Highlands of Cameroon, and form part of a chain of mountains from Bioko to Plateau State, Nigeria, with altitudes measuring over 2000m a.s.l.

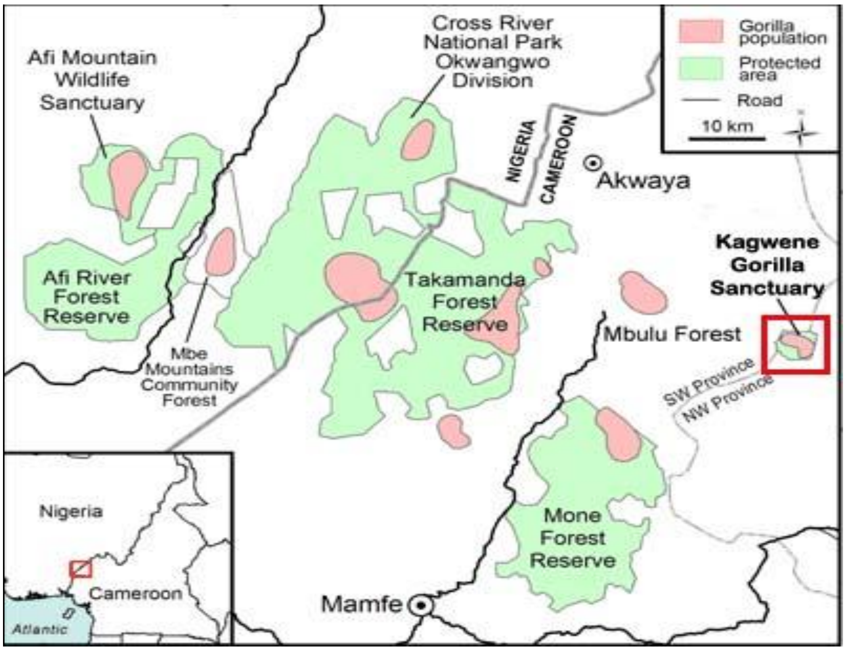



Figure 2: The Kagwene Gorilla Sanctuary

(Sunderland-Groves *et al.* 2009).

Climate is marked by a rainy season (April to October), and a dry season (November to March). Average annual rainfall is about 3,774mm; with mean temperatures ranging between 14.6˚C and 22.3˚C (Kagwene Research Camp long-term records, 2003-2008). The KGS has a dense drainage network, constituting a watershed that supplies all the communities around it. Vegetation is composed of grassland and galleries of montane forest. The area supports a variety of plant and animal species. It is a protected area, and home of the critically endangered Cross River gorilla (*Gorilla gorilla diehli*). The Wildlife Conservation Society (WCS) Takamanda-Mone Landscape Project (TMLP) runs a research camp in the sanctuary, and has collected and filed gorilla nest site data since 2003. The gorilla population in the KGS is genetically distinct from other CR Gorilla groups, but although they seem to be isolated from gorillas of other localities, genetic analyses still reveal some migration to other neighbouring populations still occur (Bergl 2006; Bergl and Vigilant 2007). Daily gorilla tracking reveals that the gorillas range in two bands of six (called Minor (M) group) and eight (called Major (J) group). The sanctuary is surrounded by nine rural settlements.

## 3.2 Materials

### 3.2.1 Analysis tools.

The primary tool used for data analysis was the `R` statistical software version 2.12.1 (R Development Core Team 2009). Several packages within the `R` environment were used for reading data and performing analysis, but the principal package for implementation and statistical analysis was `spatstat`. Nest site data were collated and formatted using Microsoft Office Excel. ArcGIS was used for preliminary visualization of data layers, and preparation of covariates. The covariates were exported from ArcGIS environment as American Standard Code for Information Interchange (ascii) files and read into `R`. Microsoft Office was used for final reporting of results.

### 3.2.2 Gorilla nest site data.

We utilized 640 nest site locations recorded in the Kagwene Groilla Sanctuary collected between 2006 and 2009 for the analysis. These locations were generously provided by the Wildlife Conservation Society Takamanda-Mone Landscape Project (WCS-TMLP) Cameroon. These data are collected during daily gorilla tracking in the sanctuary. The researchers go out each day, follow the gorilla trails until they get to the site where the gorillas built their nests. The number of nests per site differs (usually more than one), but only one GPS record (point) is taken at each site. It is therefore necessary to emphasize that this analysis is based on NEST SITE locations and not NEST locations.

The gorillas in the KGS are known to range in two bands (groups) called the Major (J) group and the Minor (M) group. For the purpose of this analysis, we classified nest sites with less than or equal to 6 nests as Minor group and sites with more than 6 nests as Major. Data were split into various categories and properties extracted for each category. Point pattern categories analyzed during this project were as follows (Table 1):

Table 1: Point pattern categories used for analysis.

| **Name** | **Description** | **Point type** | **Window** |
|---|---|---|---|
| `all.nests` | All nest sites irrespective of season and group. | Unmarked | Irregular |
| `dry.nests` | Nest sites in the dry season | Unmarked | Irregular |
| `wet.nests` | Nest sites in the rainy season | Unmarked | Irregular |
| `major.nests` | All nest sites for Major group. | Unmarked | Irregular |
| `minor.nests` | All nest sites for Minor Group. | Unmarked | Irregular |
| `all.nests.m` | All nest sites marked by gorilla group | Multitype | Irregular |
| `dry.nests.m` | Dry season nests marked by gorilla group | Multitype | Irregular |
| `wet.nests.m` | Wet season nests marked by gorilla group | Multitype | Irregular |

Our interest was to verify the properties and model the distribution of all gorilla nests for all years, for each season and for each gorilla group. All nest site locations from April to October were classified as wet season and nest locations from November to March were classified as dry season nests.

### 3.2.3 Covariates (Predictor variables).

Seven environmental covariates or explanatory variables were used for the study. The focus was to verify how these covariates explain nest site location by the gorillas. It was intended that these covariates would reflect the natural environment as much as possible, although there was an exception of disturbed forest. The covariates were as follows:

a. *Elevation:* This was the digital elevation of the study area derived from a 30m digital elevation model (DEM) obtained from ASTER (freely available for the whole world – Aster GDEM). Values were in meters.
b. *Heat Load Index (Beer's Aspect):* Calculated from the DEM using the ArcToolbox "Topography". This characterizes the landscape into the potential heat that will be incident at any point on the terrain. It implements the formula:

$$Heat\ Load = 1 + \cos((45^{o} - aspect)/slope\ degree).$$

The index ranges from 0-2, and is set to maximum for NE slopes which is the coolest slope. We reclassified the indices derived into:

- 0 to 0.999 = South slopes ----- Warmest.
- 1 to 1.999 = NW/SE slopes --- Cool.
- 2 = NE Slopes ------- Coolest.

c. *Aspect:* This was calculated from the DEM using the surface analysis provided by the ArcGIS Spatial Analyst tool.

d. *Slope degree:* This was calculated from the DEM using the surface analysis provided by the ArcGIS Spatial Analyst tool.

e. *Slope position:* Calculated from the DEM using the ArcToolbox "Topography". It classifies the slope into six landform categories (Valley, Toe Slope, Flat, Mid slope, Upper slope and Ridge).

f. *Distance from water channel:* This was a measure of the Euclidean distance away from a water channel, expressed in meters.

*g.* *Vegetation type:* This was a broad classification of vegetation into 6 categories as shown on Table 2.

Table 2: Vegetation (habitat) categories adopted for the study.

| Vegetation category | Description |
|---|---|
| Primary forest | Consists of tall, mature trees with a closed canopy, usually tall undergrowth herbs. |
| Secondary forest | Forest recovering from human disturbance, trees are younger and smaller, many saplings, high undergrowth herbs and usually very open canopies. |
| Transition vegetation | Unique vegetation found at the forest-grassland interface. Species usually consists of *zingiberaceae* and bracken fern. |
| Colonizing forest | Forest showing recovery from natural disturbance, usually with young trees, varied understorey composition and broken canopy. |
| Highly-disturbed forest | Forest showing evidence of high human disturbance such as farms under canopy. |
| Grassland | No trees, ground layer of grass sometimes mixed with shrubs. |

Sources: (Neba 2008; Sunderland *et al.* 2003; Wiseman 2008)

### 3.3 Methods.

Figure 3 shows a flow chart of the overall methodology implemented in this study.

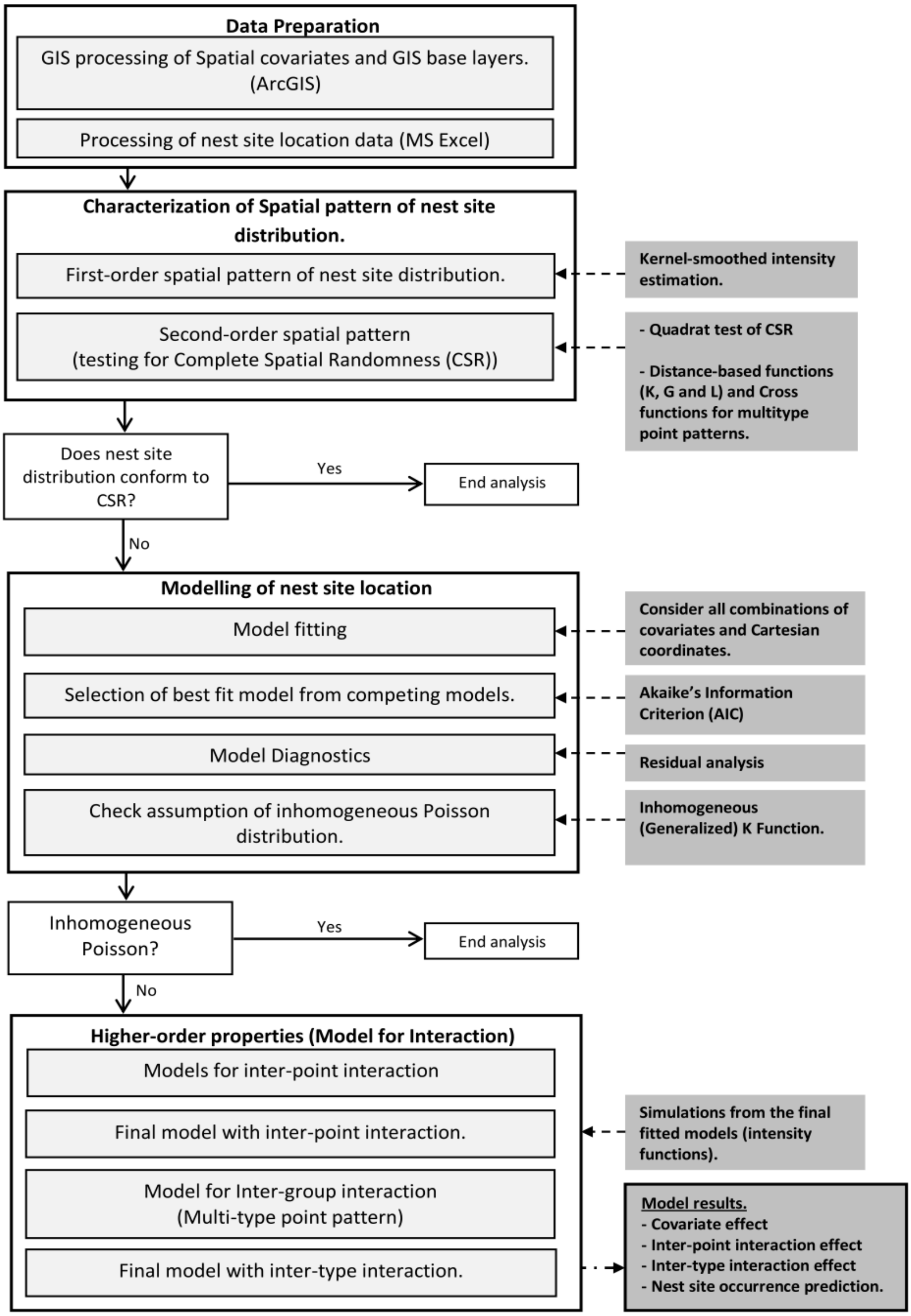



Figure 3: Flow chart of overall methodology implemented in analysing nests site data and fitting mode

### 3.3.1 Characterization of gorilla nest site distribution.

*First-order characteristics.*

First-order characteristics are characteristics related to variations in the mean value of the spatial process. They are a measure of the distribution of events in the study area (Bivand *et al.* 2007; Diggle 2003; Møller and Waagepetersen 2003). First-order characteristics do not provide any information on interaction between events in the point pattern, but yield a general idea about their spatial distribution; that is they only provide information on the global spatial trend of point distribution. This characteristic was provided by estimation of the kernel-smoothed intensity of the different point pattern categories. That is, given each point pattern, the kernel-smoothed intensity was used to estimate the general location of events. The Kernel-smoothed intensity is represented by a function λ(u), which measures the mean number of events per unit area at the point *u*. Therefore for a general location *s* and a given dataset *X*, the kernel-smoothed intensity is given by

$$\lambda_b(s) = \frac{1}{C_b(s)} \sum_{i=1}^{n} K_{ib}(s - x_i)$$

Equation 1: Kernel-smoothed intensity estimation.

where $K_b(\ )$ is a kernel with band $b > 0$, and $C_b(\ )$ is an edge correction factor (Diggle 2003; Yang *et al.* 2007).

*Testing for Complete Spatial Randomness.*

*a. Second-order characteristics of nest site distribution.*

Besides *first-order* properties, *second-order* characteristics provide information on event interaction in a point pattern. Second-order properties are thought to offer the best way to present, statistically, the distributional information inherent in point patterns and in explaining the correlation between them (Illian *et al.* 2008). Because they consider the relationship between points at different distances, *second-order* properties are credited for being able to estimate the distributional correlation between points at long range, far beyond the nearest neighbors only. In this study, Ripley's *K function* and Besag's *L function* (a transformation of the *K function*) were used to obtain the *second-order* characteristics and test for Complete Spatial Randomness of gorilla nest site distribution.

The main idea behind the *K function* (Ripley 1977) is the consideration of the average number of points found within a distance *r* from a typical point. If $\lambda K(r)$ denotes the mean number of points in a disc of radius *r* centered around a typical point $x_i$, and *n* denotes the number of points found in a window $W$, and $n_i(r) = N(b(x_i, r)\backslash\{x_i\})$ is the number of points of $N$ that occur within a distance $r$ from the typical point $x_i$, then excluding $x_i$ itself,

$$\pi(r) = \frac{1}{n}\sum_{i=1}^{n} n_i(r)$$

Equation 2: estimate of the K function

estimates $\lambda K(r)$. Therefore,

$$\lambda K(r) = E(\text{number of events within a distance } r \text{ of an arbitrary event})$$

where $E(\ )$ is the expectation operator and $\lambda$ is the intensity or the mean number of points per unit area.

The *L function* is a transformed (variant) form of Ripley's *K function.* It is defined as

$$L(r) = \sqrt{\frac{K(r)}{\pi}}$$

Equation 3: The L function

Clearly, it yields the same information as the *K function*, but is assumed to have some advantages in that when testing for Complete Spatial Randomness, it is easier to visualize the graph of the *L function* than its *K* counterpart. It is also known that for increasing distances *(r)*, there is increasing fluctuation in the estimated *K function*, a fluctuation that is stabilized by the root transformation provided by the *L function* (Illian *et al.* 2008).

The observed behavior of $K(r)$ and its transformation, $L(r)$ with respect to $\pi r^2$ is expected to yield information on the nature of interaction between points in a point pattern. Where $K(r)>\pi r^2$ or $L(r)>\pi r^2$, it indicates a clustered point process where the typical point $x_i$ has some very near neighbors and the local point density around $x_i$ is larger than the number of points per unit area ($\lambda$) in the point process. $K(r)<\pi r^2$ or $L(r)<\pi r^2$ indicates that the typical point $x_i$ is isolated and the local point density around it is smaller than $\lambda$; while $K(r)=\pi r^2$ or $L(r)=\pi r^2$ indicates a random process. Larger differences between $K(r)$ and $\pi r^2$ (and therefore between $L(r)<\pi r^2$) indicate greater clustering or regularity in point distribution, as the case may be.

The computed *K function* and *L function* were not only compared to the theoretical functions under CSR, but also the upper and lower bounds of envelopes simulated independently under CSR, but having the same intensity as the test data. Envelopes are also used together with the distance-based functions such as the *K and L functions* to test for goodness-of-fit of fitted models (Baddeley 2008; Baddeley and Turner 2000; Bivand *et al.* 2007).

This study used 99 simulations of CSR to compute envelopes. Ninety-nine simulations are recommended for point process modeling and considered conventional and analogous to alpha level $(\alpha) = 0.01$ in classical statistics (and 19 simulations would be analogous to $\alpha = 0.05$) (Illian *et al.* 2008). Deviations of the computed functions from the theoretical functions would suggest clustering (contagion) or regularity (inhibition) in nest site distribution, where, as mentioned before, $K(r) > \pi r^2$ and $L(r) > \pi r^2$ suggest clustering and $K(r) < \pi r$ and $L(r) < \pi r^2$ suggest regularity. In `spatstat`, the *K function*, *L function* and envelopes are computed by built-in functions `Kest`, `Lest` and `envelope` respectively.

The reasons for testing for CSR were generally 3-fold: (1) A rejection of CSR is a prerequisite for any further modelling of an observed point pattern, (2) testing for CSR helps us explore a data set and formulate alternative hypothesis and (3) CSR serves as a dividing hypothesis between clustering and regularity. Under CSR, there is equal probability for all events occurring at any position in the study region; and the position of each event does not in any way affect the position of any other event (events are independent).

*b. Quadrat-counting test of CSR.*

Quadrat counting tests were also used to test for the hypothesis of Complete Spatial Randomness (CSR). Quadrats were determined by different levels of covariates. The quadrat test utilizes a chi square ($\chi^2$) test of hypothesis to verify whether or not for different levels of covariates, observed nest site frequency differed significantly from expected frequency. The tests were carried out at $\alpha = 0.05$. In `spatstat`, the quadrat test is provided by the formula `quadrat.test`.

### 3.3.2 Model fitting to data.

Models were fitted to estimate an intensity function that could best describe each of the point patterns.

*1. Homogeneous Poisson Process (HPP).*

These are the null (stationary) models that assume a uniform distribution of points within the study area (*W*). They can also be described as *isotropic* (Bivand *et al.* 2007) where the occurrence of an event does not affect the occurrence of another within the study area. Intensity ($\lambda$) is constant in *W*, and the *second-order* properties only depend on the relative positions of two points (Bivand *et al.* 2007). HPP can be formally described as having the following characteristics:

a. The number of events in a region $W$, with area $|W|$ is a Poisson distribution with mean intensity $\lambda|W|$, where $\lambda$ is the constant intensity of the point process.

b. The number of events $n$ occurring in an area $W$ area uniformly distributed in $W$. (Baddeley 2008; Bivand *et al.* 2007).

Null models were therefore fitted for each point pattern with the assumption that spatial trend was neither influenced by any covariate nor point coordinates.

*2. Modeling for an Inhomogeneous Poisson Process (IPP).*

In case CSR was out-ruled, it was assumed (tentatively!) that nest site locations were independent, that is, their distribution (or location probability) depended on heterogeneity of selected environmental variables and/or Cartesian coordinates of their locations and not on interaction between them (that is the assumption of an IPP). All possible combinations of environmental covariates were considered as candidate models (using the `R` package `combinat` to generate all possible combinations), and a Maximum Pseudolikelihood Estimation (MPLE) method was used to estimate coefficients for each candidate model. This method has been described as efficient, sufficient and consistent (Illian *et al.* 2008). MPLE is simply an approximation of maximum likelihood estimation (MLE) and is recommended for point process modeling because for many spatial point process models, the likelihood is intractable. The `R` package `spatstat` implements the MPLE using the Berman-Turner computational algorithm (Baddeley and Turner 2000; Berman and Turner 1992). It fits point process models to point data in terms of their Papangelou conditional intensity, loosely defined as the probability of an event occurring at point $u$ given that the rest of the process coincides with the point pattern **X** (Baddeley and Turner 2000). Intensity is estimated as:

$$\lambda(u,x) = \beta(u)$$

Equation 4: Conditional intensity function.

where $\beta(u)$ depends on the spatial locations of $u$, and therefore stands for "spatial trend", or environmental covariates. That is, the term $\beta(u)$ can be a function of the Cartesian coordinates of $u$ or of an observed covariate at location $u$, or of a mixture of both (Baddeley 2008). We first considered combinations of covariates alone, and if model diagnostics proved that the fitted models were still inadequate to explain the spatial trend, it showed that these covariates were not enough to explain nest site distribution in the sanctuary, and that there was still a spatial trend inherent in the data that was not captured by the model. In this case, Cartesian coordinates of the nest sites were introduced as a covariate to substitute for other factors that might have an effect on intensity but were not available for the analysis (such as temperature, rainfall, other human factors etc), and to enable the model capture any spatial trend caused by such factors in nest site distribution (Baddeley 2008; Yang *et al.*

2007; Rathbun *et al.* 2007). By implication therefore, it was assumed here that spatial trend of nest site distribution in the sanctuary was influenced by environmental covariates and other factors not considered in the model. Inhomogeneous spatial trend was modelled with intensity that is log-quadratic in continuous covariates (elevation, water distance and slope) and Cartesian coordinates. Polynomials of up to the order two were considered (as long as it converged with the MPLE) (Baddeley and Turner 2000; Yang *et al.* 2007). The log-quadratic intensity function in Cartesian coordinates and continuous covariates was estimated as:

$$\log \lambda_\theta(u, x) = \theta_0 + \theta_1 B(u) + \theta_2 B(u)^2$$

or equivalently,

$$\lambda_\theta(u, x) = \exp(\theta_0 + \theta_1 B(u) + \theta_2 B(u)^2)$$

Equation 5: Conditional intensity function as a log-quadratic of continuous variables.

where $\theta_1$, $\theta_2 \ldots \theta_n$ estimated parameters, and *B(u)* represents spatial trend or covariate. The log-quadratic intensity function is fitted through the formula `polynom` formula in `spatstat`.

### 3.3.3 Model selection.

The different possible combinations of environmental covariates for modeling gave a total of 127 competing candidate models for each nest site point pattern category. From these, the model that could best describe the observed pattern of nest site distribution had to be chosen. The Akaike's Information Criterion (AIC) was used for this purpose (Akaike 1973). It is defined as:

$$AIC = -2\max(\log - likelihood) + 2k$$

Equation 6:Akaike's Information Criterion.

where *k* is the number of parameters in the model. The AIC is a handy method of selecting the best of competing models over goodness-of-fit because it minimizes the effect of model complexity (increased number of parameters) in selecting the better model.

### 3.3.4 Model diagnostics and verification of assumption of inhomogeneity.

Residual analysis was used to validate the best fit models for each nest site category. Lurking variable plots were computed for each model, plotting the cumulative Pearson residuals of the model against each of the continuous covariates (elevation, distance from water channel and slope percent) and Cartesian coordinates. If the model were a good fit, then the cumulative Pearson residuals should approximate to zero (an analogy to the fact that residuals for a regression model always sum up to zero in classical statistics such as `GLM`) and when plotted for each continuous variable should fall within the error bands ($2\sigma$ bands).

The goodness-of-fit of models was also tested by computing envelopes from simulations of the fitted models and observing the behaviour of the computed *K function.* We utilized the *generalized* (inhomogeneous) version of Ripley's *K function* (Baddeley *et al.* 2000) and 99 simulations to test for goodness-of-fit of the models (Baddeley and Turner 2000). Ripley's *K function* is defined only for stationary (homogeneous) point processes, but for non-stationary process, it is necessary to utilize a function that accounts for inhomogeneity. The generalized (or inhomogeneous) *K function* therefore is, as the name implies, a generalisation of Ripley's *K function* to suite inhomogeneous processes (Baddeley 2008). These are implemented in `spatstat` through the functions `envelope` and `Kinhom`.

### 3.3.5 Modelling for inter-point interaction (Higher-order properties).

In all the models fitted before (including covariate and Cartesian coordinate effect), diagnostics (both residual plots and inhomogeneous K functions) still showed that the models were inadequate to explain the spatial trend in nest site distribution, and that the assumption of an IPP was not adequate. This therefore was a motivation for fitting higher-order models for the data. The aim of this was to verify interaction between points. It was assumed that the spatial distribution of nest sites could be explained by spatial covariates and as well as interaction between nest site locations. An interaction parameter could therefore be added to the fitted intensity function, in which case the function will take the form:

$$\log \lambda_\theta(u,x) = \theta_0 + \theta_1 B(u) + \theta_2 B(u)^2 + \theta_3 C(u,x)$$

or equivalently,

$$\lambda_\theta(u,x) = \exp(\theta_0 + \theta_1 B(u) + \theta_2 B(u)^2 + \theta_3 C(u,x))$$

Equation 7: Conditional Intensity including interaction parameter.

where $\theta_1, \theta_2 \ldots \theta_n$ are estimated parameters, *B(u)* represents spatial covariates or Cartesian coordinates and *C(u, x)* represents the inter-point interaction term.

The Area Interaction model was chosen amongst different options such as the Strauss process (Strauss 1975) and the Geyer saturation process (Geyer 1999) to fit models portraying higher-order properties of gorilla nest site distribution. It was chosen over the Strauss process because, although the model was originally meant to describe clustering between points in a point process and is credited for being a prototype to cluster models, further research (Kelly and Ripley 1976; Turner 2009) has demonstrated that mathematically, it is not an adequate process to model interaction because the density of such a process for a point pattern $X=\{x_1, x_2, \ldots x_n)$ is not integrable, unless $n$ is fixed. It has also been argued that unlike the Strauss process, the Area-Interaction process is not based on a simple pair-wise interaction but on a much more complex structure of interactions (Baddeley 2008; Illian *et al.* 2008). The Area Interaction model was also chosen above the Geyer's saturation process simply because it portrayed less computation time in `R`.

The area-interaction process with a disc of radius *r* is defined as a point pattern process with probability density given by:

$$f(x_i,...,x_n) = \alpha k^{n(x)} \eta^{-A(x)}$$

Equation 8.: Probability density function of an Area-Interaction process.

where $x_i,...,x_n$ are the points in the point pattern, *k* is the intensity parameter, η is the interaction parameter and *A(x)* is the area of the region created by the union of discs or radius *r* centred at the points $x_i,...,x_n$ and *α* represents a normalizing constant (Baddeley and Van Lieshout 1995).

In `spatstat`, the Area-Interaction process is implemented by the function `AreaInter`. In this process, the aim was to obtain the interaction parameter eta (η). Values of η < 1 suggest an 'ordered' or 'inhibitive' pattern; if η > 1, then the model describes a clustered or attractive pattern. If η = 1, then there is no interaction between points, and the pattern corresponds to a Poisson process. If η = 0, then a *hardcore* process is encountered in which there are no points within the *hardcore* distance (*r*) of any point in the point process; that is, there is total inhibition (Baddeley and Lieshout 1995; Turner 2009).

*Estimation of the interaction radius (r) ("nuisance or irregular parameter").*

In fitting Area Interaction models, it is very important to determine an adequate value for the irregular parameter – the interaction radius. This parameter has been described as a 'nuisance' parameter because it is usually not clear how it is derived statistically. In fact, in the R package `spatstat`, the model function `ppm` does not provide a direct estimation of this parameter. It has to be determined by some other method. It is an intricate part of the model fitting process because wrong values of the interaction parameter can cause an overestimation or underestimation of the model. (Baddeley and Turner 2000) propose that this parameter can be obtained by maximizing the profile log pseudo-likelihood for the dataset. We tried interaction radii for each dataset between 100 and 1150 by 115 steps for profile maximization. The upper bounds (1150) were chosen based on the inhomogeneous K functions (`Kinhom`) of each point data set. This was the maximum distance obtained from the inhomogeneous distance function. For each dataset therefore 10 interaction models were fitted and in each case, the maximum log pseudo-likelihood for each point pattern was obtained. In `R`, the function `profilepl` built into the `spatstat` package fits the models for estimation of this parameter.

### 3.3.6 Simulating the fitted models.

The final selected models for each point pattern included covariates, Cartesian coordinates and inter-point interaction. Simulations were made of these final models, and if the model were good enough, then the simulated points would be very similar to the original points when displayed on plots. Simulations were done using the Metropolis-Hastings algorithm (Chib and Greenberg 1995), implemented in `spatstat` by the function `rmh`.

### 3.3.7 Predictions from the fitted models.

The final fitted models were used to make predictions on gorilla nest site location; that is, using the final fitted models, we evaluated the spatial trend at new locations. It would be important to verify where else gorilla nest sites would occur, given the fitted model, thereby using known gorilla locations and information generated from the model (covariate effect and inter-point interaction) to obtain information about unknown nest site locations. This is provided by the function `predict.ppm` in `spatstat` (Baddeley and Turner 2000).

### 3.3.8 Modelling for Inter-type interaction (Multi-type Point Pattern analysis).

Previous analysis and models ignored the fact that gorillas in the sanctuary range in two groups (bands). However, there was need to consider this and model nest site distribution in terms of interaction between the two groups of gorillas – the Major group and the Minor group. We therefore created bivariate point patterns in which each nest site location was given an additional attribute – the gorilla group to which it belonged. This is a Multi-type (bivariate) Point Pattern.

We sought to answer the following question: Are Major group nest sites clustered around Minor group nest sites or are they farther apart, OR is the pattern of occurrence of one type of event related to the occurrence of the other OR does the distribution of Major group nest sites explain the distribution of Minor group nest sites OR is there evidence that the Major and Minor group nest sites occur independently? To answer this question, we used analogues of the K and L distance functions described for simple point patterns in the preceding sections. The null hypothesis here was: There is no inter-group interaction, ie $\gamma_{major,\ minor} = 1$. If Major group nests occur independently or Minor group nests, then $Kmajor,\ minor\ (r) = \pi r^2$ and $Lmajor,\ minor(r)=\pi r^2$. Under repulsion, $Kmajor,minor\ (r)<\pi r^2$ ($Lmajor,\ minor(r)<\pi r^2$) and under attraction, $Kmajor,\ minor(r)>\pi r^2$ ($Lmajor,\ minor(r)>\pi r^2$). In `spatstat`, these estimations are provided by the summary functions `Kcross` and `Lcross` for *Kmajor,minor* and *Lmajor,minor* respectively. They are used to test for Complete Spatial Randomness and

Independence (CSRI) for a marked point pattern and they incorporate both characteristics of *random labelling* (given the point locations X, marks are conditionally independent and identically distributed (iid)) and *independence of components* (ie the sub-processes *Xm* of points of each mark *m*, are independent point processes) (Baddeley 2008; Baddeley and Turner 2000).

To fit models to the multi-type point patterns, we used the best fit models chosen for point pattern analysis (described in the preceding sections) and included marks as a factor. Inhomogeneous multi-type Poisson process models assumed that nest sites of each type (Major or Minor group) portrayed a different, non-constant intensity. Intensity was therefore modelled as a log-quadratic function of Cartesian coordinates of nest sites and environmental covariates, multiplied by a constant factor depending on the mark (Baddeley 2008; Baddeley and Turner 2006). Inhomogeneous multi-type models were therefore fitted where intensity function $\lambda(x,y,m)$ at location $(x,y)$ and marks $(m)$ satisfies

$$\log \lambda \ ((x, y, m)) = \alpha_m + \beta_m u$$

Equation 9: Conditional intensity for multi-type point process.

where $\alpha_m$ and $\beta_m$ are model parameters and *u* represents the value of spatial covariates, xy location of nest site or a mixture of both. Final selected models were also tested for goodness-of-fit using the *K function* for bivariate point patterns, implemented by `Kcross.inhom` in `spatstat`. It counts the expected number of points of type *major* within a given distance of a point of type *minor* taking into consideration varying intensities of the different types. In cases where the inhomogeneous functions still showed that the models were inadequate, we went ahead to model for higher-order properties where inter-type interaction was considered. Here, quite unfortunately, the only model currently implemented in R for fitting higher-order interaction for marked point patterns is the Strauss model. We therefore computed the models, but bearing in mind that the resulting coefficients and simulations might not be the best for the data, given the weaknesses of the Strauss process pointed out in preceding sections of this chapter (section 3.3.5).

From the fitted coefficients, the inter-type interaction coefficients were obtained for each point pattern, and intensity functions including inter-type interaction were obtained. Other procedures such as simulating the resulting models and predictions from the fitted models were as described for the univariate spatial point processes above.

# CHAPTER 4: RESULTS OF ANALYSIS.

## 4.1 First-order characteristics of gorilla nest site distribution in the sanctuary.

A plot of the kernel-smoothed intensity for all nest site data revealed a "hot-spot" at the central extending to the northwestern part of the sanctuary, and a "cold-spot" towards the southeastern (Figure 4). These suggest that the point pattern is not completely random and is far from homogeneous, but follows another point process.

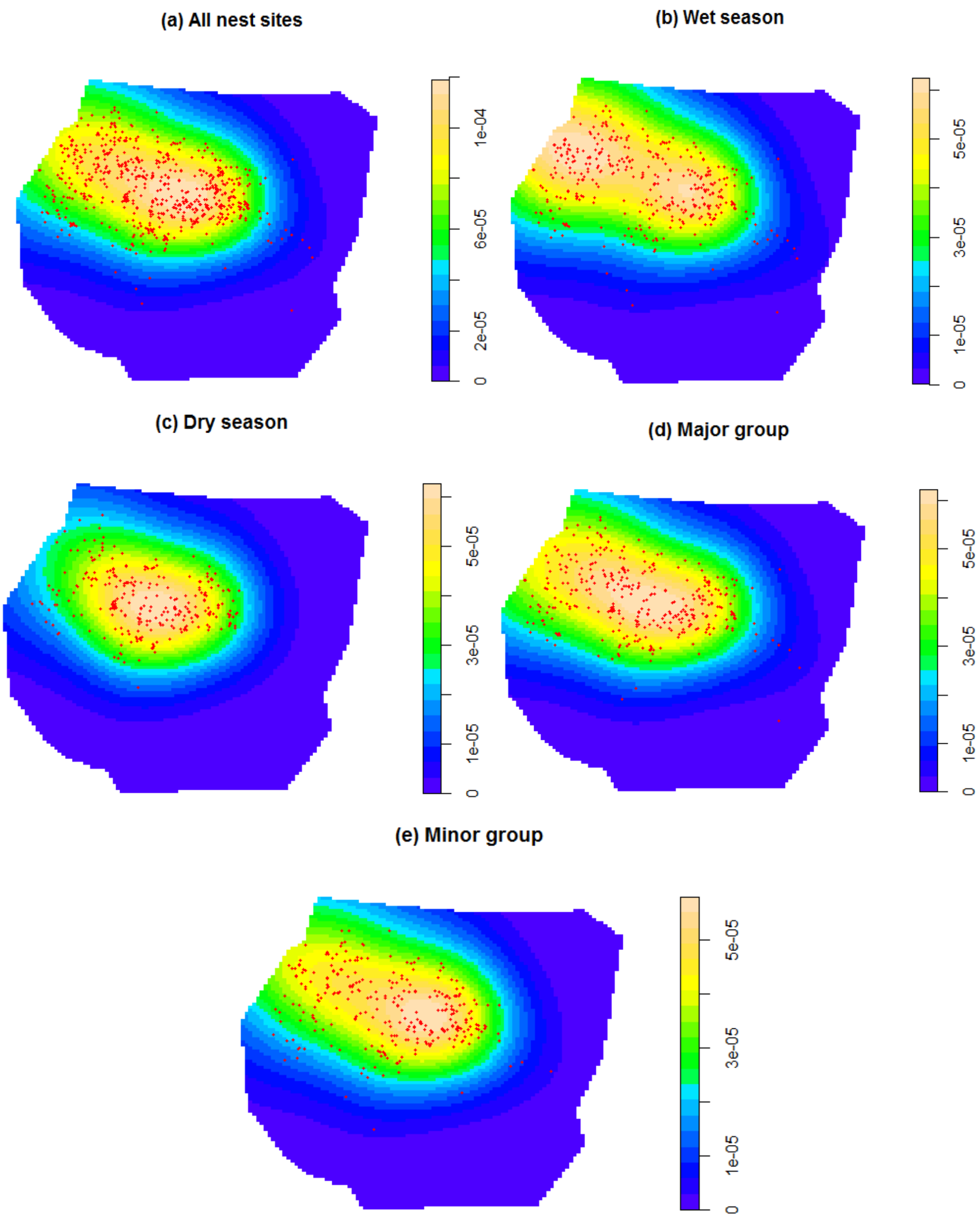


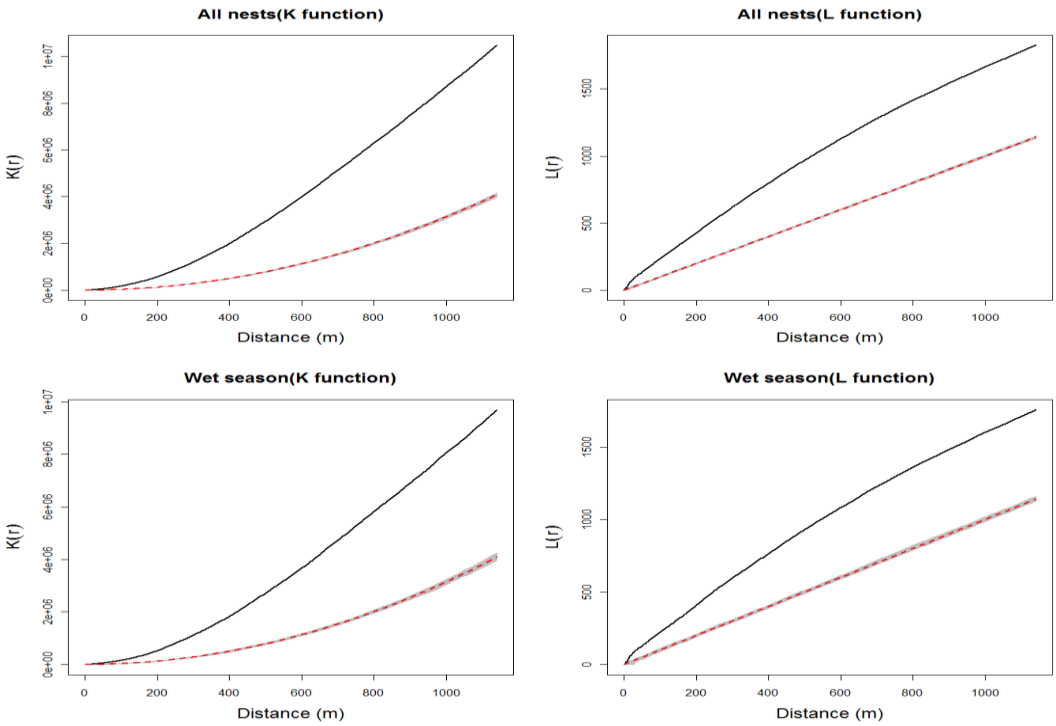

Figure 4: Kernel-smoothed intensity for different point patterns.

The results revealed by the kernel smoothed intensities suggest that the point patterns for all nests, wet season nests and dry season nests, and nests for both major and minor groups follow a spatial trend that is different from uniform or stationary. That is, they suggest that nest site distribution is not *isotropic* in the plane. However these are only suggestive and more empirical formulations need to be carried out before we can totally out-rule complete spatial randomness.

## 4.2 Testing for Complete Spatial Randomness in nest site distribution.

As mentioned before, the main reason for verifying *second-order* characteristics of nest site distribution was to test for CSR. The null hypothesis was that nest site distribution conforms to CSR or is a realization of CSR. The alternative was that nest site distribution is not a realization of CSR, but of another unspecified point process that is not completely random. Chi square statistics obtained from quadrat-count test for different nest site categories revealed significant difference in nest site distribution, given different levels of elevation, aspect, vegetation type, percent slope and distance from water body (Appendix A). This suggested that nest site distribution in the sanctuary is not completely random.

The figures below show envelopes computed from 99 simulations of the null hypothesis (Figure 5), used to further test for CSR.



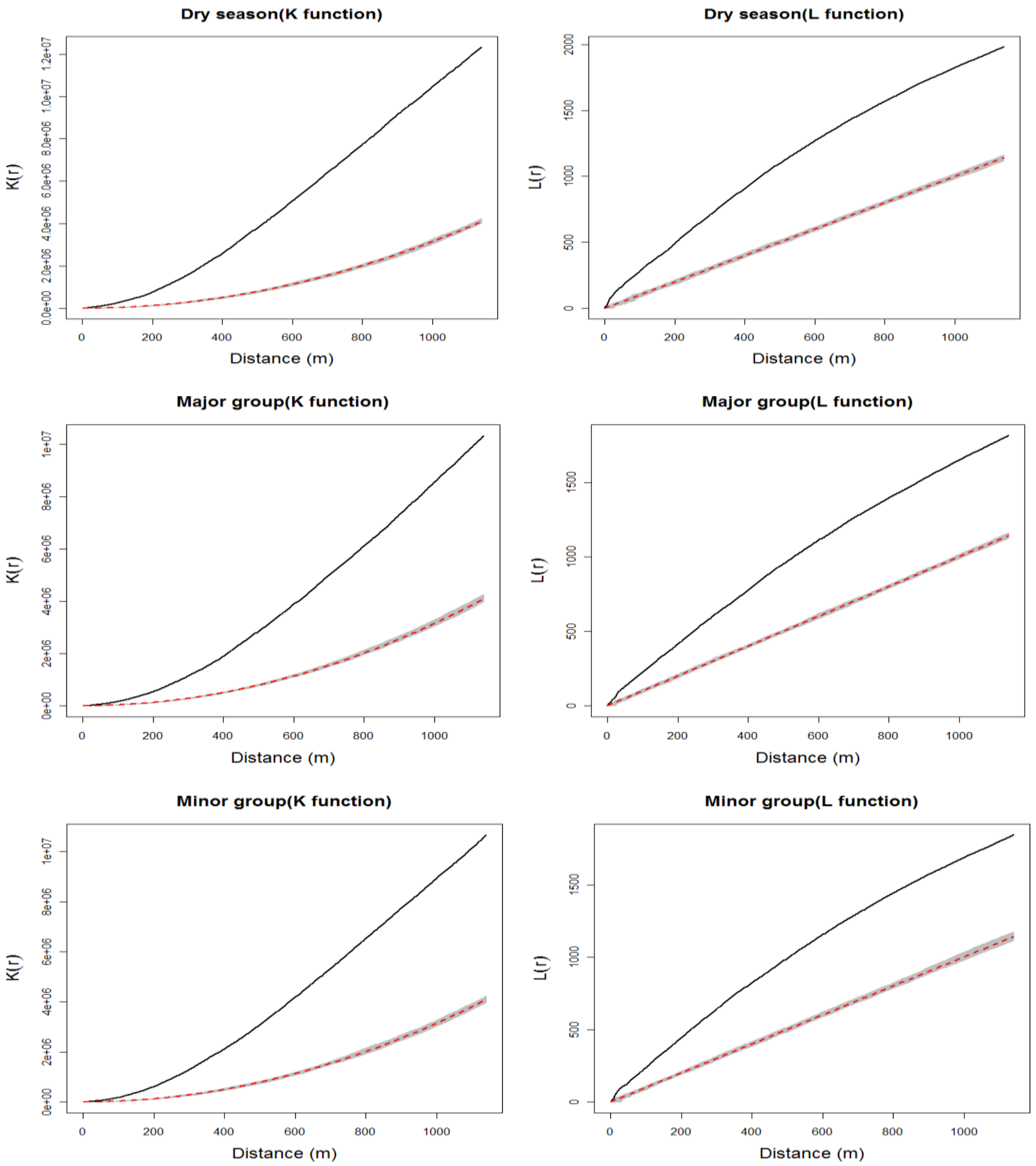



Figure 5: Second-order summary K and L functions for different nest site categories. The black line indicates the empirical K function while the grey band indicates the envelope from 99 simulations.

Simulated envelopes using the three distance functions, K and L revealed glaring evidence against the null hypothesis of CSR for all categories of nest sites. The observed distribution of all data sets fall outside the computed envelopes, suggesting that the data do not follow or conform to a completely spatial random Poisson Process. In all cases, from a scale of about 100 meters or less, the empirical K and L functions are larger than the CSR theoretical K and L functions, that is $K(r) > \pi r^2$, and $L(r) > \pi r^2$, indicating a clear departure from CSR towards spatial clustering (attraction or contagion) among nest site locations for all years, for each gorilla group (Major and Minor) and for each season (Wet and Dry).

Following this result, the null hypothesis of CSR is rejected. We therefore conclude that gorilla nest site distribution in the sanctuary is not completely random, but shows evidence of clustering and there is need for further modelling of the data to verify whether or not distribution pattern depends on environmental covariates (point independence), or on interaction between points (dependence) or both. Models fitted to the data actually suggest that this clustering could depend on environmental heterogeneity as well as interaction between points.

## 4.3 Model fitting and diagnostics.

### 4.3.1 Models of homogeneity (stationary Poisson models).

Table 3 shows the uniform intensity values (number of nest sites / square meters) for the null model (HPP) and the corresponding AIC values. This set of models will, hereinafter be referred to as Ho models.

Table 3: Constant intensity values for the various point pattern categories.

| **Point pattern** | **Uniform Intensity (points per $m^2$)** | **AIC** | **Number of parameters** |
|---|---|---|---|
| Ho All nests | $3.22 \times 10^{-5}$ | 14521.6 | 1 |
| Ho Wet season nests | $1.85 \times 10^{-5}$ | 8736.265 | 1 |
| Ho Dry season nests | $1.38 \times 10^{-5}$ | 6683.094 | 1 |
| Ho Major group | $1.73 \times 10^{-5}$ | 8233.414 | 1 |
| Ho Minor group | $1.49 \times 10^{-5}$ | 7173.811 | 1 |

### 4.3.2 Models of inhomogeneity (Non-stationary Poisson models).

**a. Models involving covariate effect only (M1 Models).**

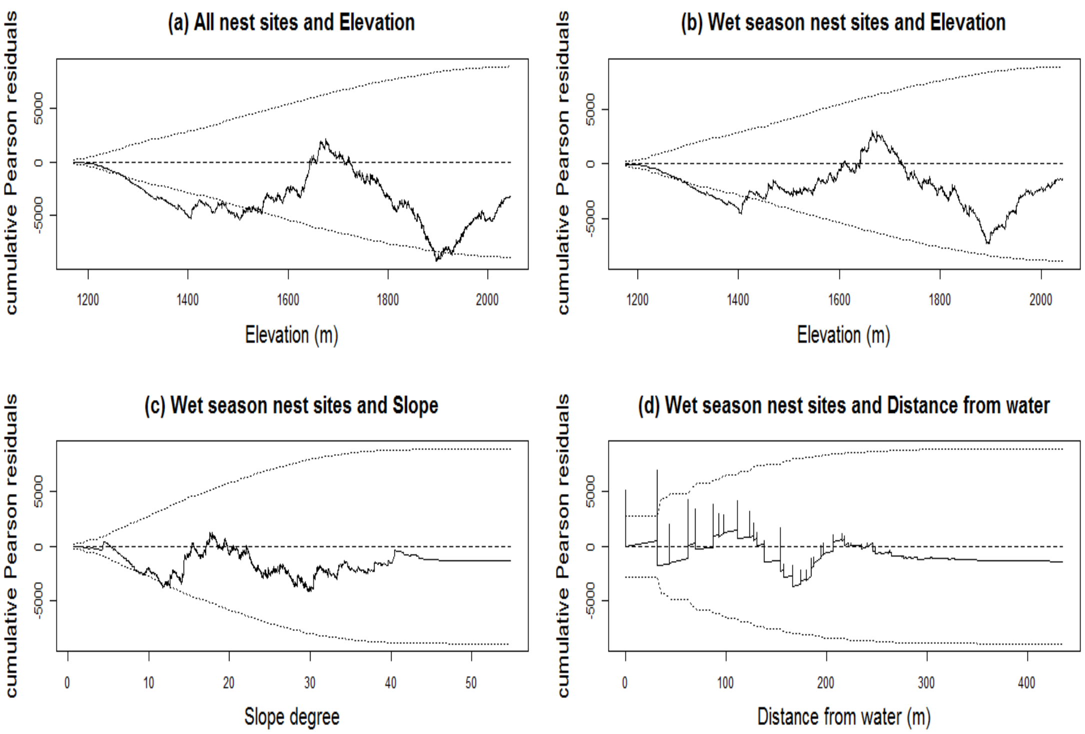
Models of inhomogeneity were fitted to verify if the distribution of nest sites follows an IPP. We assumed (tentatively!) that nest site distribution depended on environmental heterogeneity and/or Cartesian coordinates, and not on interaction between points. The first set of IPP models fitted considered covariate effect only, without the effect of Cartesian coordinates of the points. The best fit model of the 127 candidate models was selected using the AIC, in which case the model with the smallest AIC for each point pattern was considered the best fit for that point pattern. Table 4 shows the summary of these models (hereinafter referred to as M1 models).

Table 4: Summary of best fit models of inhomogeneity with covariates only (M1 Models).

| Model | AIC | No. of parameters | Formula |
|---|---|---|---|
| **M1 all nests** | 13662.06 | 24 | *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(slope position) + *f*(heat index) + *f*(vegetation) |
| **M1 dry season** | 6230.93 | 17 | *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(vegetation) |
| **M1 rainy season** | 8269.863 | 19 | *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(vegetation) + *p*(water distance, 2) |
| **M1 Major group** | 7806.22 | 17 | *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(vegetation) |
| **M1 Minor group** | 6759.79 | 17 | *p*(elevation,2) + *f*(aspect) + *p*(slope degree,2) + *f*(vegetation) |

*p* signify Polynomial order while *f* signifies that the covariate was modeled as a factor.

Residual analysis of M1 models (lurking variable plots) revealed that the best-fit models were still inadequate to explain nest site distribution (Figure 6). For instance, the cumulative Pearson residuals for all nest sites are lower than the 5% significance bands at elevations between 1300-1500 meters (Figure 6 a), suggesting an overestimation of nest site location at this elevation range by the model. Less gorilla nest sites may therefore occur at these altitudes than the model actually predicts. This is a similar flaw of most of the other models with respect to elevation.



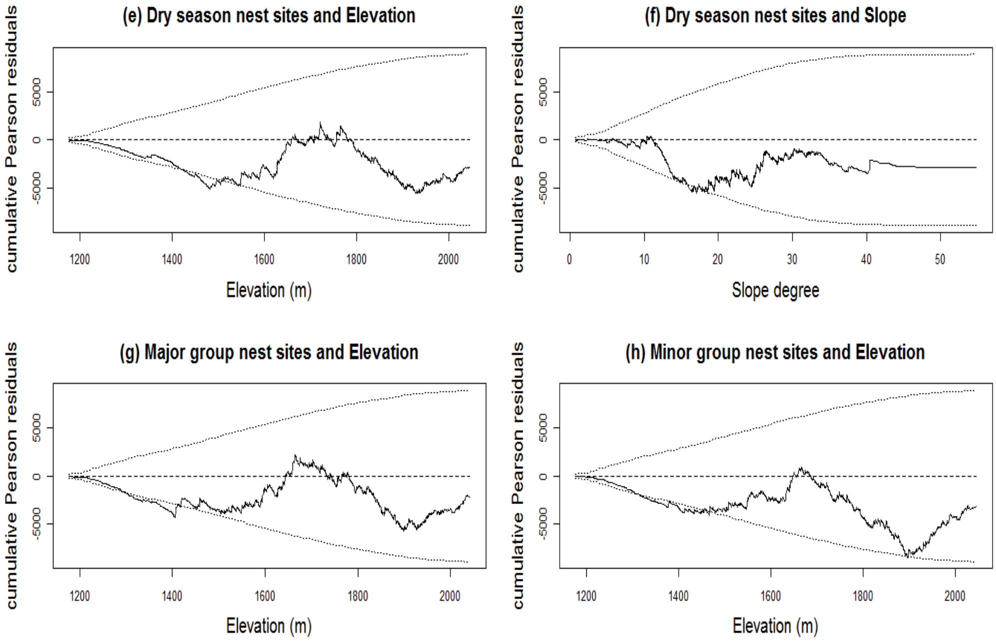



Figure 6: Lurking variable plots for models including covariates only against continuous covariates. Solid lines represent empirical cumulative Pearson residuals for each model while dotted lines represent 5% error bands.

Diagnostic plots of the cumulative Pearson residuals for each model against Cartesian (XY) coordinates also revealed glaring violation of the 5% error bounds (Figure 7). This suggested that there was a residual spatial trend that these models failed to capture. It therefore motivated the inclusion of Cartesian coordinates in to the model, in which case the intensity function was estimated as a mixture of the environmental covariates and the Cartesian coordinates as recommended in Baddeley (2008).

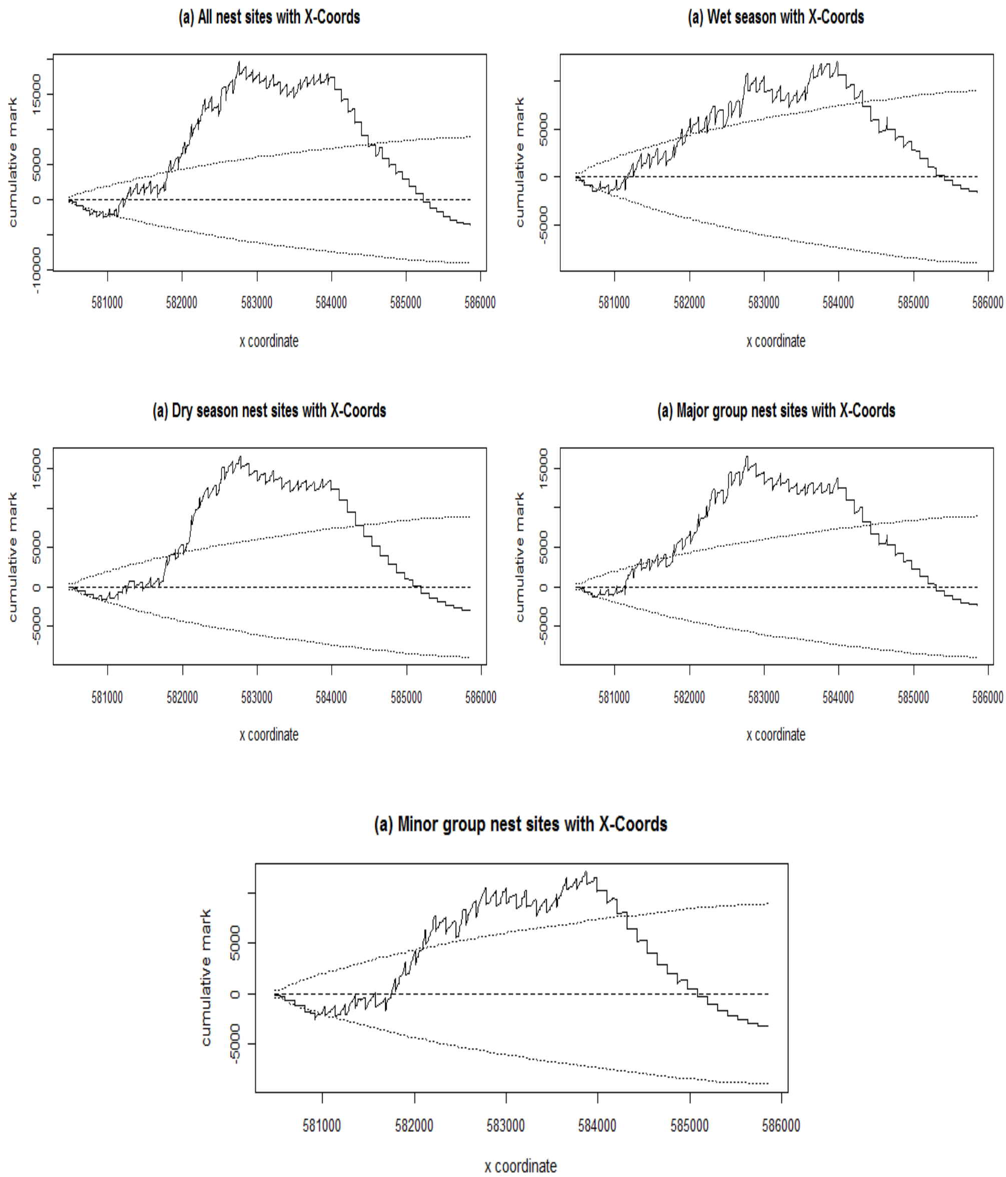



Figure 7: Cumulative Pearson residuals for each model against Cartesian coordinates. Solid lines represent empirical cumulative Pearson residuals for each model while dotted lines represent 5% error bands.

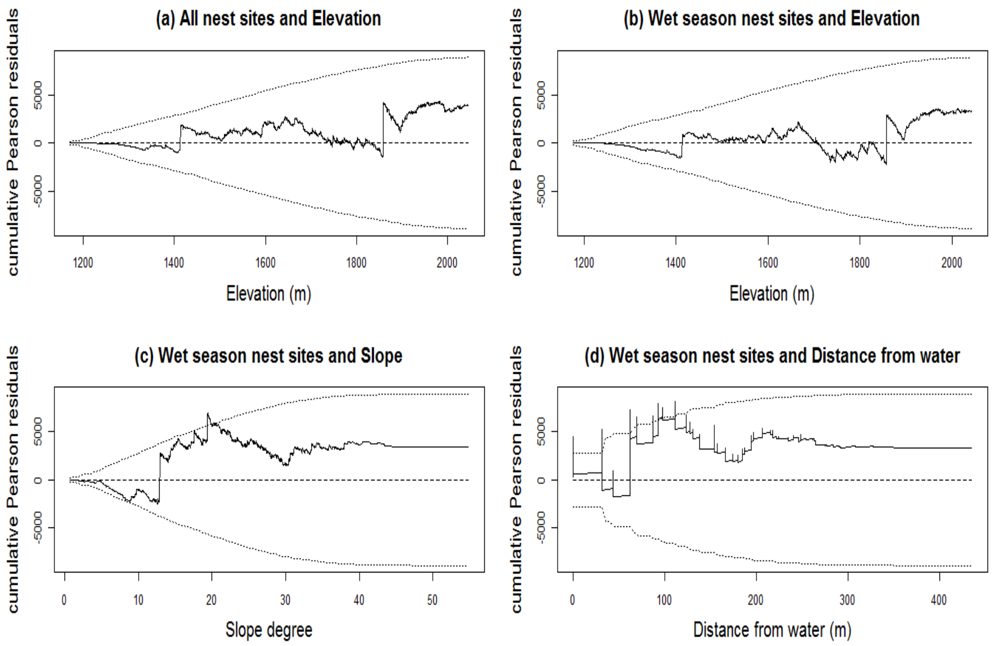
### *b. Models involving Covariates and Cartesian coordinates (M2 Models).*

The inclusion of Cartesian coordinates to the models was to capture any spatial trend caused by the point location. Table 5 shows the formulas and AIC values for these models.

Table 5: Summary of best fit models of inhomogeneity with covariates and Cartesian coordinates (**M2 Models**).

| Model | AIC | No. of parameters | Formula |
|---|---|---|---|
| **M2 all nests** | 13049.58 | 29 | *p*(x,y, 2) + *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(slope position) + *f*(heat index) + *f*(vegetation) |
| **M2 dry season** | 5889.264 | 22 | *p*(x,y, 2) + *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(vegetation) |
| **M2 rainy season** | 7988.514 | 24 | *p*(x,y, 2) + *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(vegetation) + *p*(water distance) |
| **M2 Major group** | 7462.516 | 22 | *p*(x,y, 2) + *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(vegetation) |
| **M2 Minor group** | 6485.394 | 22 | *p*(x,y, 2) + *p*(elevation, 2) + *f*(aspect) + *p*(slope degree, 2) + *f*(vegetation) |

When Cartesian coordinates were added to the models, they showed a marked improvement through lower AICs and better fit of residuals within the error bands. Figure 8 shows the residual plots (lurking variable plots) against continuous covariates and Cartesian coordinates for the M2 models.



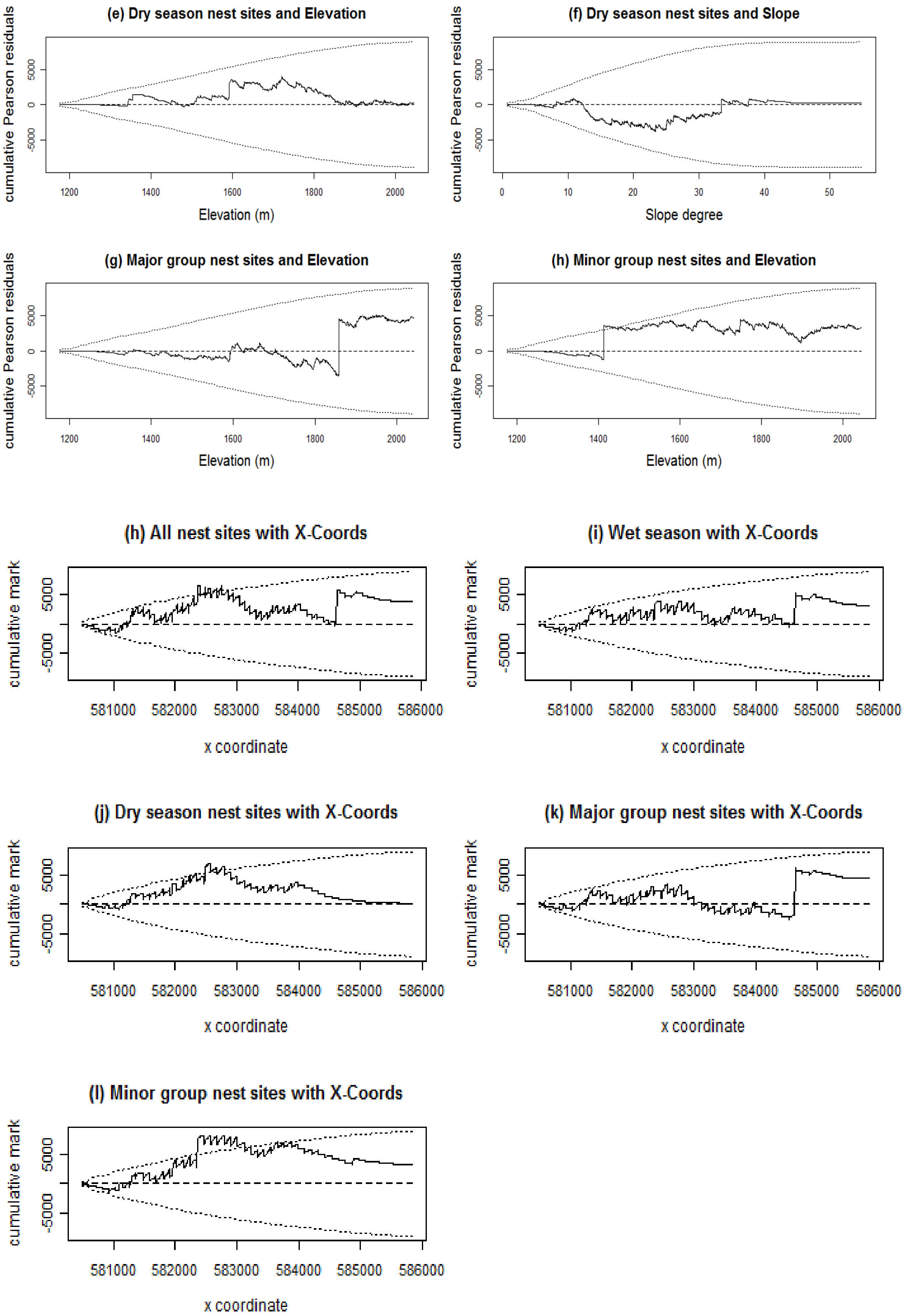



Figure 8: Lurking variable plots for models including covariates and Cartesian coordinates against continuous covariates. Solid lines represent empirical cumulative Pearson residuals for each model while dotted lines represent 5% error bands.

We therefore considered the combined models (Covariates and Cartesian coordinates, M2 Models) as better models to estimate an intensity function for nest site distribution over the M1 models.

To verify the assumption of an inhomogeneous Poisson Process (IPP), we used an inhomogeneous (generalized) *K function* to compute 99 simulations of the fitted models. Envelopes were computed from the upper and lower bounds of the simulations. Figure 9 shows the computed envelopes for each M2 model.

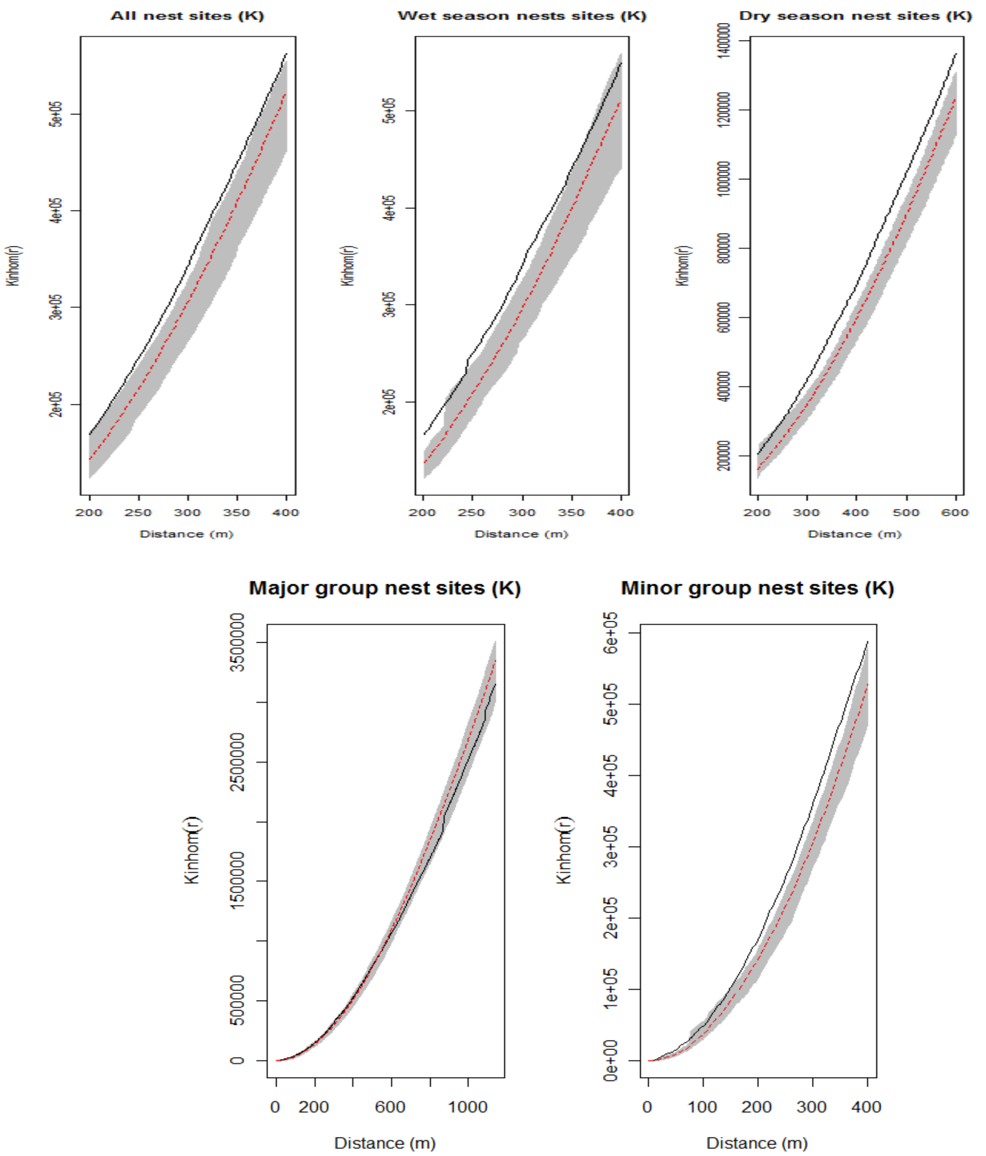



Figure 9: Generalized (Inhomogeneous) K functions with envelopes plotted from 99 simulations of the combined (M2) models.

The plots in Figure 9 have been restricted to distances (r) where the empirical K functions fall out of the simulated envelopes to create a zoom effect. The functions show that the M2 model (combined model) fits perfectly for Major group nest site locations, but still falls short to explain the trends in the other gorilla nest site point pattern categories. Therefore, even after accounting for clustering due to covariates and Cartesian coordinates, there still appears to be some clustering that is unexplained for by the models. This therefore indicates the need to estimate higher-order properties for all nest site categories. Even though at this point the Major group nest sites appear to follow an IPP, it was necessary to further verify that no interaction exists between points as well by fitting higher-order models. If truly the data follows an IPP, then the interaction parameter eta ($\eta$) should be equal to one (given that $\eta = 1$ reduces the interaction model to a Poisson process). Also, if truly the IPP model is better than the higher-interaction model, then we would expect a lower AIC value for the IPP model than for the higher-interaction model fitted to the same data.

### 4.4 Higher-order properties of Gorilla Nest Site distribution.

The Area Interaction process was chosen to estimate higher-order properties of nest site distribution over the Strauss and Geyer Saturation processes for reasons mentioned in the preceding chapter.

The interaction radii obtained by maximising the log Pseudo-likelihood for each nest site pattern are shown on Figure 10. The interaction radius is maximized at 330m for dry season nest site point patterns, and 100m for all other point patterns. These were the values used as the interaction radius (r) in meters for fitting the Area Interaction models for the different datasets.

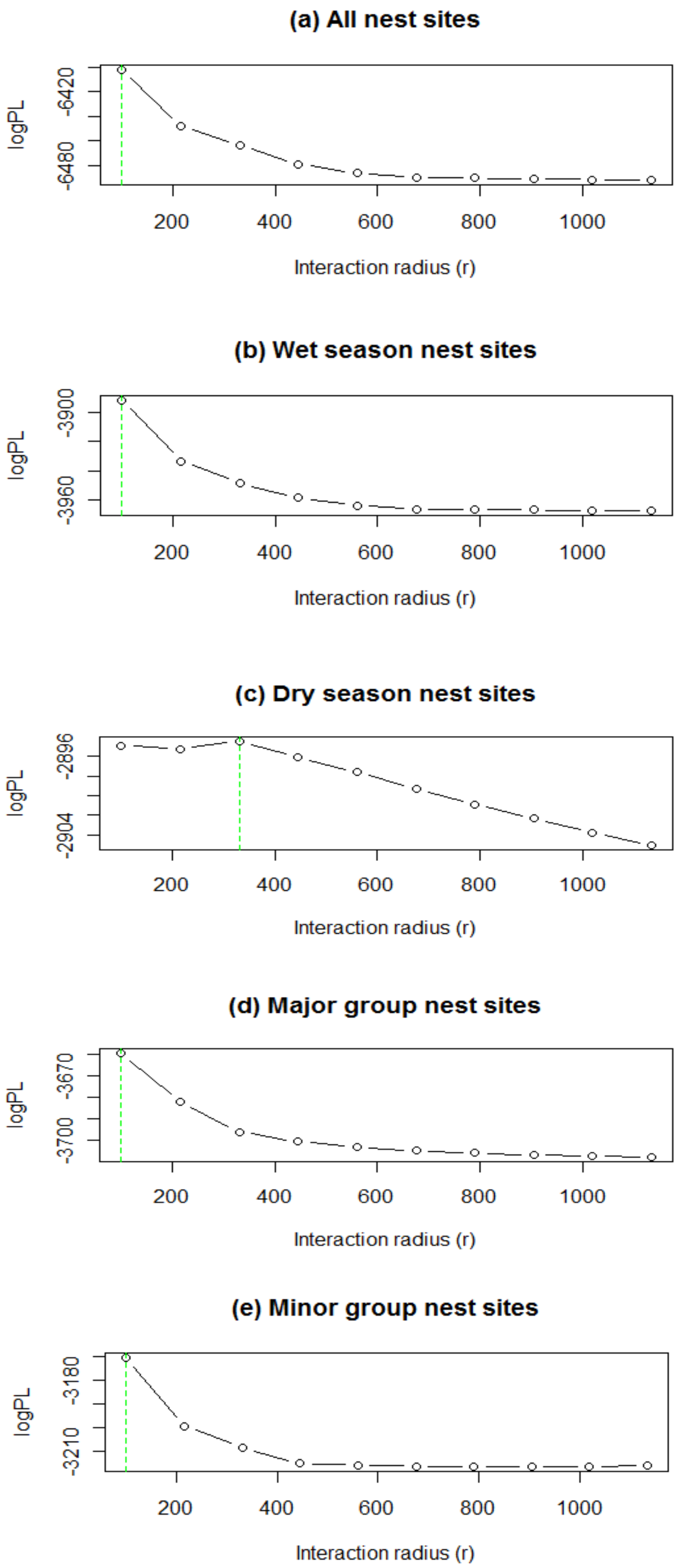



Figure 10: Pseudo-likelihood profiles for estimating values of the irregular parameter (interaction radius) for the Area Interaction model. Green dashed line shows the *r* values at which pseudo-likelihood was maximized.

The fitted interaction models for the different point patterns were as follows (Table 6).

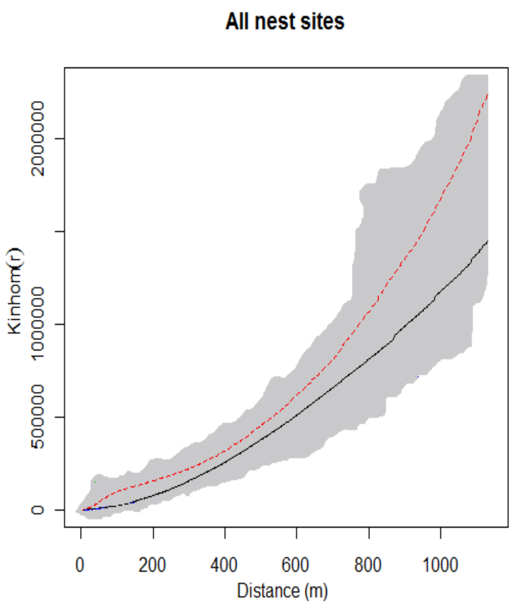
Table 6: Fitted parameters for the Area Interaction model.

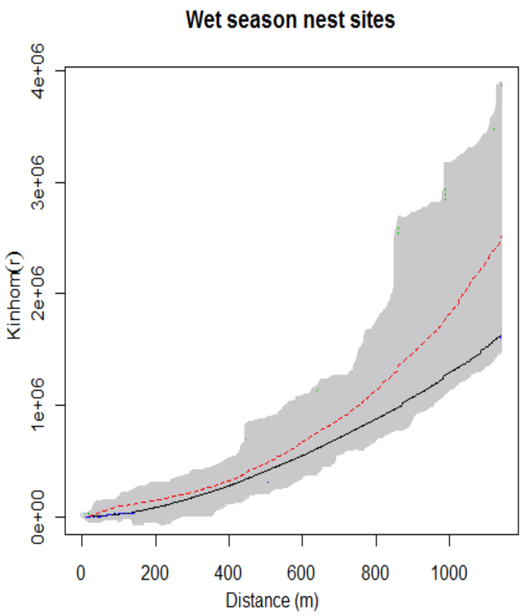
| Model | Interaction radius (r) (m) | Fitted interaction parameter eta (η) | AIC | No. of parameters | Interaction coefficient |
|---|---|---|---|---|---|
| M3 All nests | 100 | 30.2598 | 12848.06 | 30 | 3.40982 |
| M3 Rainy season | 100 | 18.8847 | 7825.346 | 25 | 2.938354 |
| M3 Dry season | 330 | 10.0016 | 5839.803 | 23 | 2.302746 |
| M3 Major group | 100 | 14.665 | 7355.395 | 23 | 2.685461 |
| M3 Minor group | 100 | 14.1361 | 6391.193 | 23 | 2.648729 |

The addition of inter-point interaction to the model improves on the AIC value of the models. It was therefore assumed that these models better estimate an intensity function for the different point patterns.

In the final interaction models (M3 models), the interaction parameter eta (η) is far greater than one for all nest site patterns. This indicates that there is strong attraction between nest site locations, and that the distribution pattern is highly clustered.

The following figures (Figure 11) show plots from the *K functions* and the simulated envelopes (99 simulations) used to further verify the model fitness.



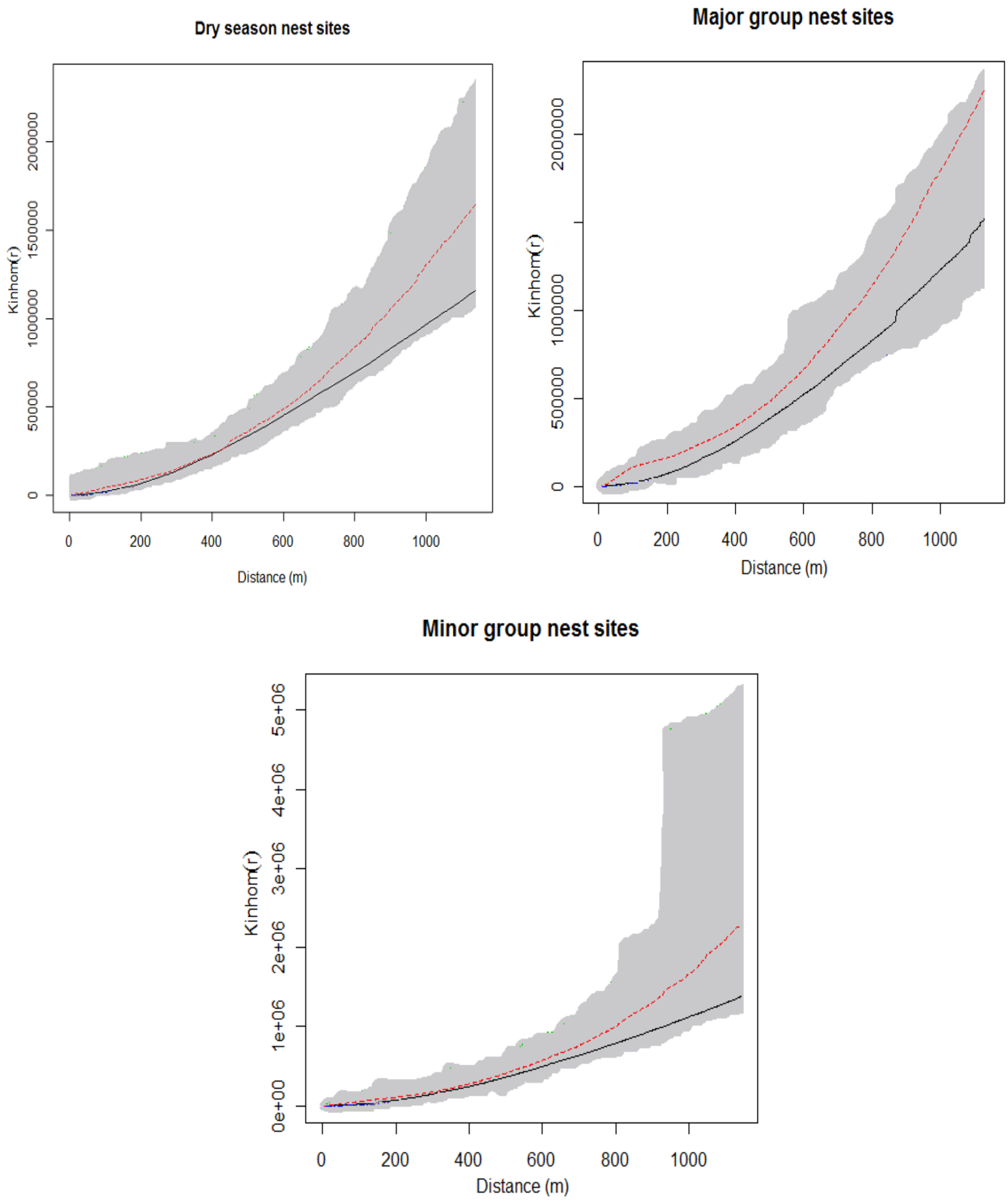



Figure 11: Generalized *K* Functions for the final trend plus interaction models. The shaded region (grey) represents envelopes from 99 simulations of each model, while the black solid line represents the empirical function from the fitted model.

As shown on Figure 11, the empirical *K function* lies within the simulated envelopes in all nest site categories and along all distances. This suggests that the M3 models are good enough to estimate an intensity function for nest site distribution in all nest site categories. It was therefore concluded at this stage that nest site distribution in the sanctuary is a function of environmental covariates and interaction between the points.

### 4.5 Simulation of the final fitted models.

Simulations produced from the best fit models (M3 models) showed a very closely similar picture of the simulated point patterns and the original point patterns as shown in the following plots (Figure 12). The results from these simulations therefore further confirmed that the M2 models plus trend were suitable to explain trend and interaction gorilla nest site distribution in the Kagwene sanctuary.

The simulations motivated the conclusion that the M3 models are good enough to estimate an intensity function for gorilla nest site data in the sanctuary.

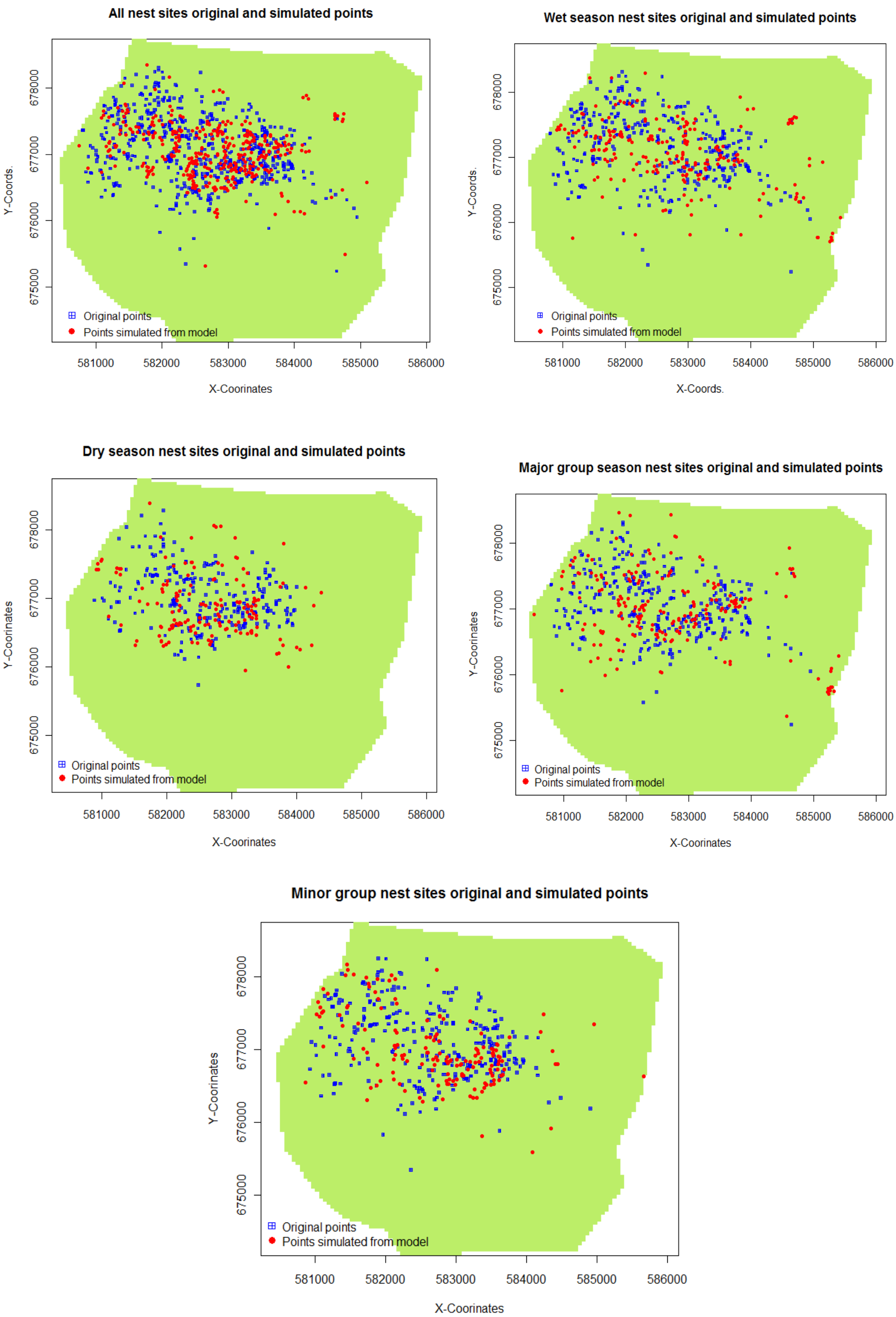



Figure 12: Original nest site locations (Blue) and simulated locations (Red) from the final trend plus interaction models for the different nest site categories in the Kagwene Sanctuary.

The coefficients of the predictor variables for the final fitted models (M3 models) are presented on Table 7.

Table 7: Coefficients of predictor variables in final (Covariates + interaction) models.

| | Factors | Nest site category | | | | |
|---|---|---|---|---|---|---|
| | | All nests | Wet season | Dry season | Major group | Minor group |
| Parameters | Intercept | -583303.5 | -578279.2 | -1198242 | -797904.7 | -777617.6 |
| | Interaction | 3.436 | 2.911 | 8.118 | 2.545 | 2.648 |
| Elevation | Elevation | -0.001 | -0.001 | -0.006 | -0.003 | -0.003 |
| | Elevation² | 0.0000005 | 0.000005 | 0.000002 | 0.000001 | 0.000001 |
| Aspect | North | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Northeast | 0.183 | 0.393 | 0.189 | 0.279 | 0.271 |
| | East | 0.537 | 0.821 | 0.533 | 0.759 | 0.716 |
| | Southeast | 0.439 | 0.378 | 0.308 | 0.056 | 0.614 |
| | South | 0.154 | -0.046 | 0.460 | -0.014 | 0.364 |
| | Southwest | 0.097 | -0.062 | 0.762 | 0.199 | 0.513 |
| | West | 0.287 | 0.244 | 0.072 | 0.090 | 0.314 |
| | Northwest | -0.076 | 0.233 | -0.00002 | 0.025 | 0.108 |
| Heat index | Coolest | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Cool | -0.085 | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Warm | -0.094 | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| Slope position | Valley | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Toe slope | -0.026 | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Flat | -0.006 | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Mid slope | 0.146 | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Upper slope | 0.183 | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Ridge | 0.135 | 0 (n/a) | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| Vegetation | Colonizing forest | 0.078 | 0.661 | -0.133 | 0.520 | 1.080 |
| | Grassland | -1.142 | -0.986 | -1.619 | -1.037 | -1.115 |
| | Primary forest | -0.573 | -0.213 | -0.914 | -0.408 | -0.429 |
| | Secondary forest | 0.429 | 0.782 | -6.889 | 1.057 | -0.128 |
| | Transition | 1.763 | 1.738 | -7.925 | 2.147 | -0.123 |
| Slope degree | Slope deg. | 0.046 | 0.068 | 0.054 | 0.035 | 0.061 |
| | Slope deg.² | -0.0009 | -0.001 | -0.001 | -0.0007 | -0.001 |
| Water distance | Distance from water | 0 (n/a) | 0.002 | 0 (n/a) | 0 (n/a) | 0 (n/a) |
| | Distance from water² | 0 (n/a) | -0.0000009 | 0 (n/a) | 0 (n/a) | 0 (n/a) |

*n/a* values indicate factor levels that had zero effect on nest site distribution. These levels were therefore eliminated from the final model formula.

## 4.6 Prediction from the final M3 model.

The M3 models considered the best fit for the dataset were used to predict gorilla nest site distribution in the sanctuary. Figure 13 (a-e) shows the predicted trend of gorilla nest site distribution from these models.

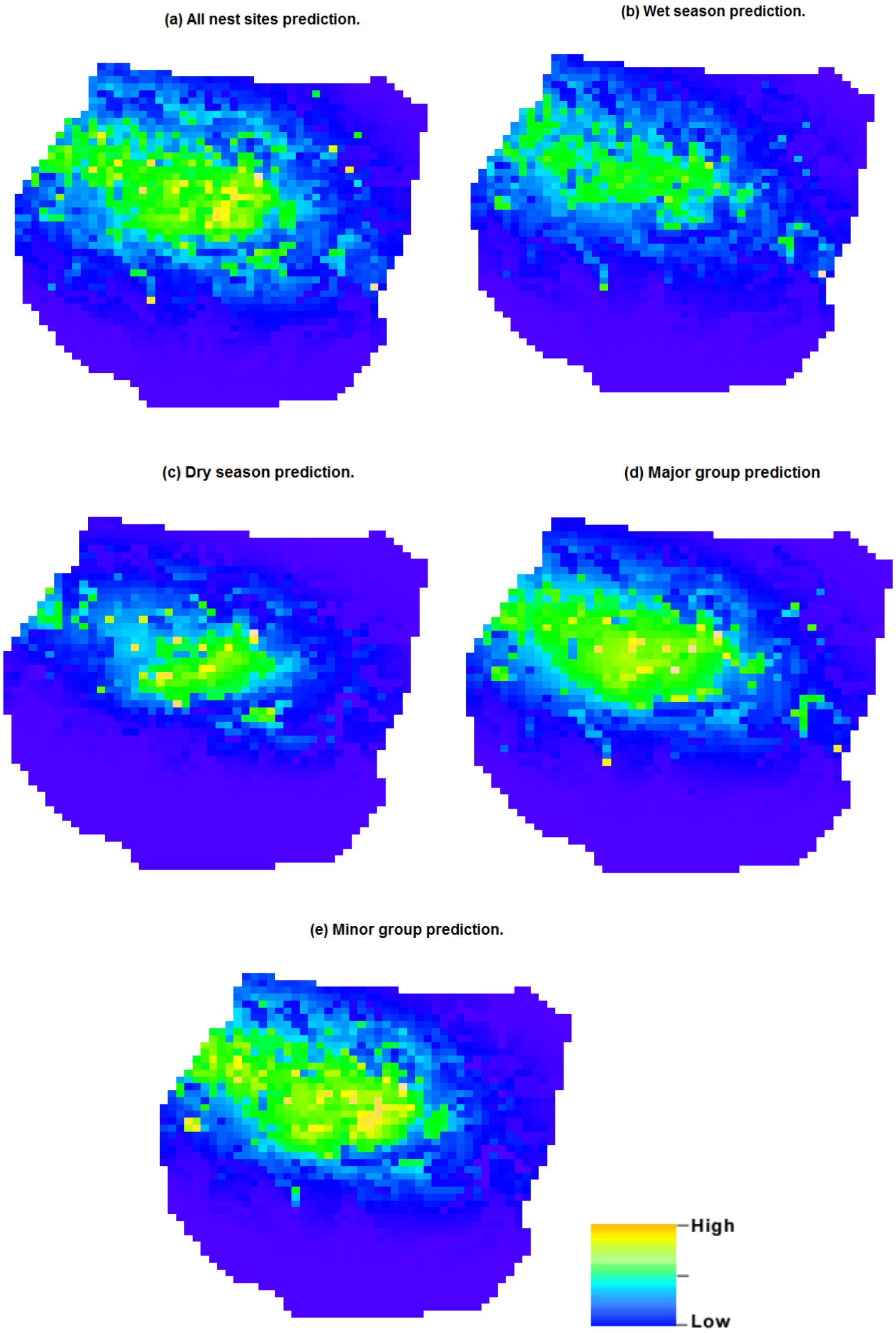



Figure 13: Predicted trend from M3 models

(Spatial covariates + XY Coordinates + Interaction between points).

### 4.7 Multi-type (Bivariate) Point Pattern Analysis.

The previous sections of this chapter stated results of univariate point process models fitted to the nest site data. This section presents results and discussions based on multi-type point pattern analysis. As mentioned in preceding chapters, the gorillas in the Kagwene sanctuary are known to range in two groups – the *Major* and the *Minor* groups. Therefore besides modeling for interaction between points, it was necessary to also verify the influence of group type on nest site location. We therefore would want to know if the location of Major group nest sites can explain the location of Minor group nest sites. This is inter-type interaction. Figure 14 shows plots of the marked point patterns.

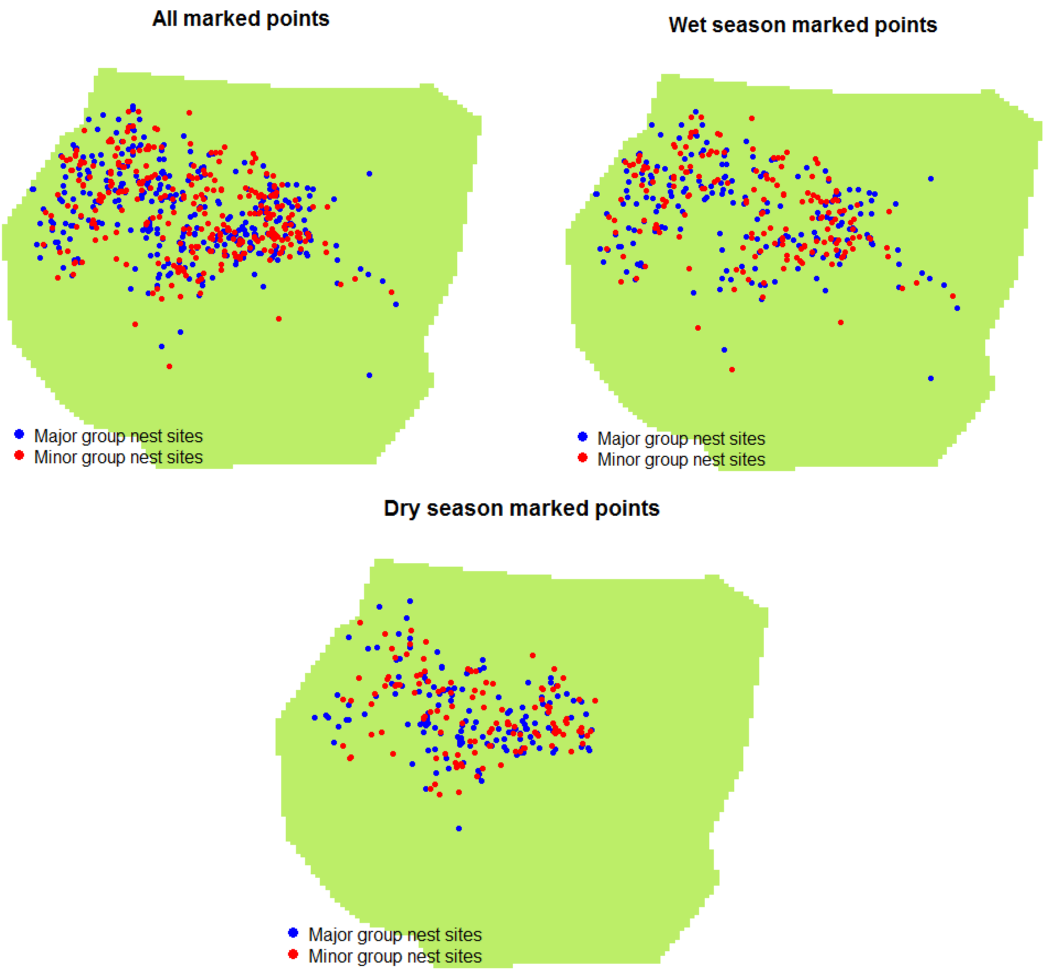



Figure 14: Marked spatial point patterns of two gorilla groups nest sites in the Kagwene Sanctuary, Cameroon.

#### 4.7.1 Summary statistics.

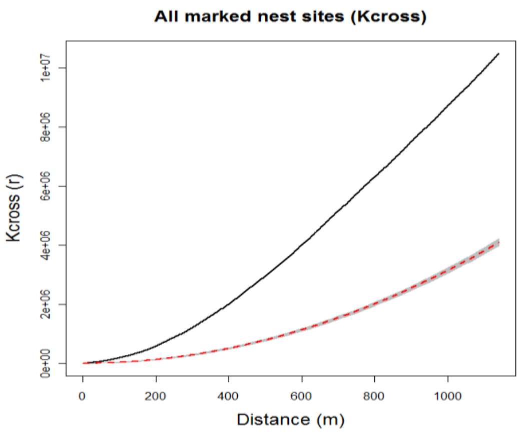
Kernel-smoothed intensity plots in the earlier part of this chapter (Figure 4) already suggested that Major and Minor group nest sites were not uniformly distributed in the sanctuary (not *isotropic*). Table 8 shows summary statistics for the two gorilla groups in the sanctuary.

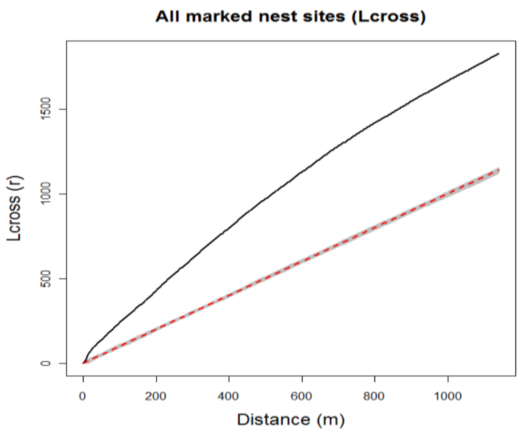
Table 8: Summary statistics of the two gorilla groups nest site data.

| Process | Nest site frequency | Proportion | Intensity |
|---|---|---|---|
| | **All nest sites** | | |
| **Major** | 344 | 0.537 | $1.73x10^{-5}$ |
| **Minor** | 296 | 0.463 | $1.49\ x10^{-5}$ |
| | **Wet season nest sites** | | |
| **Major** | 196 | 0.534 | $9.86\ x10^{-6}$ |
| **Minor** | 171 | 0.466 | $8.60\ x10^{-6}$ |
| | **Dry season nest sites** | | |
| **Major** | 149 | 0.544 | $7.50\ x10^{-6}$ |
| **Minor** | 125 | 0.456 | $6.29\ x10^{-6}$ |

### 4.7.2 Test of independence between Major and Minor group nest sites.

The summary *K and L functions* in Figure 15 all show a dismissal of the null hypothesis of CSRI. In all cases, the empirical K and L functions fall outside the simulated envelopes, suggesting that there is quite some dependence between points of the Major group and those of the Minor group. There is a clear departure from CSRI of all point processes since $Kij(r) > \pi r^2$ and $Lij(r) > \pi r^2$ at all distances. We therefore conclude that there is a dependence relationship between nest site location of Major gorilla groups and Minor gorilla groups in the Kagwene sanctuary. As $Kij(r) > \pi r^2$ and $Lij(r) > \pi r^2$, it suggests that the type of inter-group interaction is attraction.



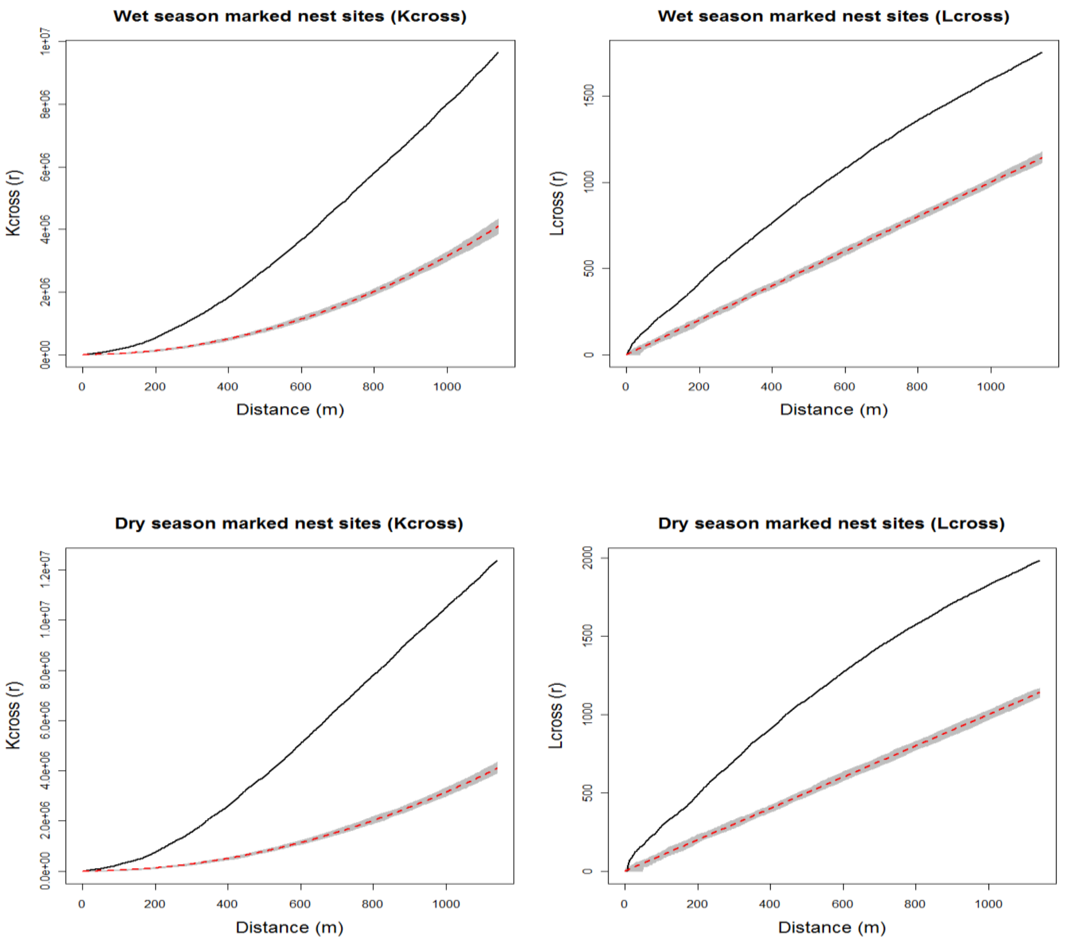



Figure 15: Second-order summary statistics for bivariate (multi-type) point pattern. The black line represents the empirical multi-type K function while the grey line indicates envelopes computed from 99 simulations of CSRI.

## 4.8 Multi-type model fitting (Multi-type trend).

### 4.8.1 Stationary (homogeneous) multi-type Poisson models (HMPP).

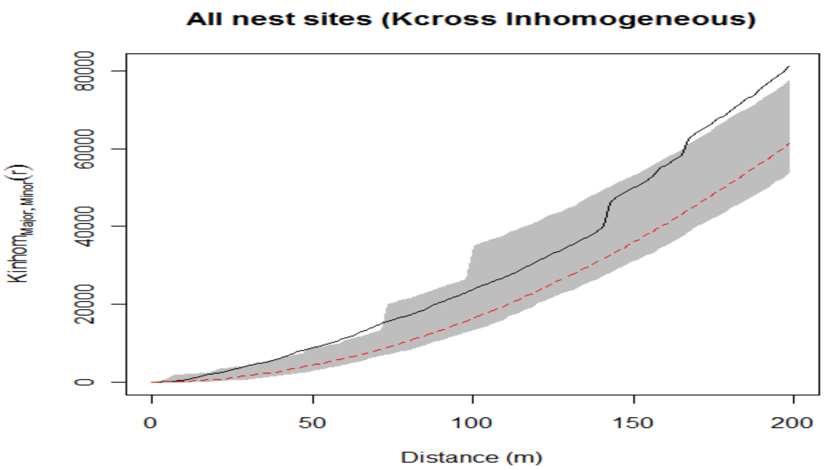
The null model for stationary multi-type Poisson process holds that there is a separate constant intensity for each mark type. In `spatstat`, the trend formula `~1` used for univariate point pattern modelling is replaced by the formula `~marks` to fit a homogeneous (stationary) multi-type Poisson model under this null hypothesis. The following intensity values were obtained from this set of homogeneous models Table 9.

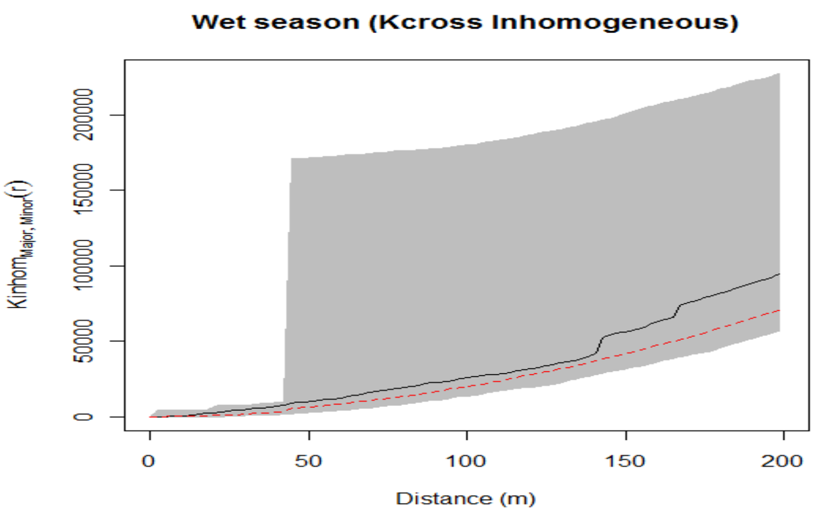
Table 9: Constant intensity values for bivariate point patterns.

| **Point pattern** | **Beta Major (points per $m^2$)** | **Beta Minor (points per $m^2$)** | **AIC** | **Number of parameters** |
|---|---|---|---|---|
| Ho All marked nests | $1.729 \times 10^{-5}$ | $1.488 \times 10^{-5}$ | 15408.18 | 2 |
| Ho Wet season marked nests | $9.849 \times 10^{-6}$ | $8.593 \times 10^{-6}$ | 9246.294 | 2 |
| Ho Dry season marked nests | $7.487 \times 10^{-6}$ | $6.281 \times 10^{-6}$ | 7063.553 | 2 |

### 4.8.2 Test for inhomogeneous Multi-type Poisson process (IMPP).

We assumed tentatively that the intensity depended on environmental covariates and type of point (marks) and fitted models to test for inhomogeneous multi-type Poisson Process. At the time of this analysis, residual analysis methods were not yet implemented in `spatstat` for multi-type models. The only option available to test for the hypothesis of inhomogeneous multi-type Poisson process was to plot inhomogeneous multi-type K functions with simulated envelopes. These are implemented in `spatstat` using `Kcross.inhom` and `envelope` functions respectively. Figure 16 presents the results of these plots.



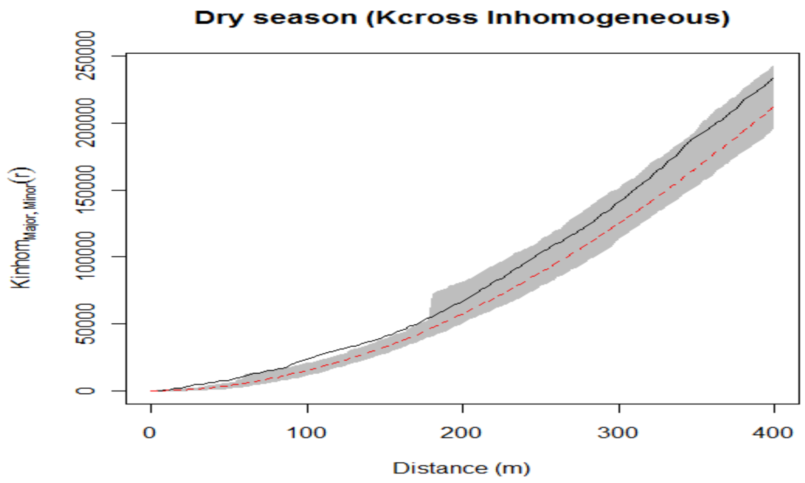



Figure 16: Inhomogeneous multi-type K functions for fitted multi-type models. The black lines represent the empirical inhomogeneous K functions while the grey bands represent envelopes computed from 99 simulations of the fitted models.

From the inhomogeneous multi-type K functions, it was observed that when marks are considered wet season nest sites show quite some conformity to an inhomogeneous multi-type Poisson process. We can therefore conclude (tentatively!) that wet season nest site distribution follows an inhomogeneous multi-type Poisson process in which case there is a different non-constant intensity function for each of the gorilla groups, which is a log-quadratic function of environmental variables. This would also suggest that there is no inter-group interaction in the wet season – but this is still subject to test. The goodness-of-fit plots also show that at small distances, between 0-200m, aggregated nest sites and dry season nest site locations do not follow an inhomogeneous multi-type Poisson process. It is therefore a motivation to fit models for higher-order properties of distribution for these nest site categories as well.

### 4.8.3 Modelling for inter-group interaction.

Even though nest sites recorded in the wet season portrayed a characteristic of an inhomogeneous Poisson Process, we went ahead to fit a higher-order interaction model on the following grounds: if nest site distribution truly follows an IPP, then a higher-order model fitted to the same data should yield a higher AIC value than that obtained for the IPP model to show that the IPP model was better, and the interaction parameter obtained (gamma) should equate to one (given that when gamma = 1, then the higher-order interaction model conforms or reduces to a Poisson process). We therefore went ahead to model for interaction between all nest site categories to verify interaction that may exist between the two groups of gorillas. We sought to answer the question: is there evidence that the Major and Minor group nest sites occur independently?

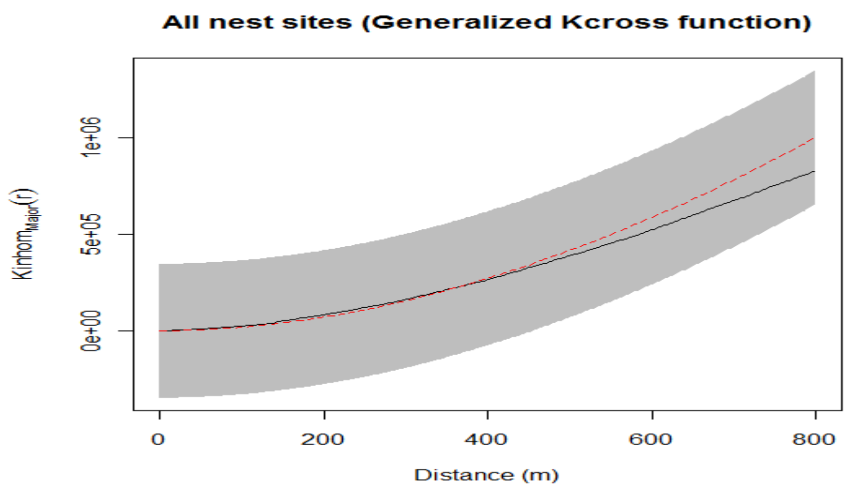
Table 10 presents gamma parameter values for interaction between nest sites of the *major* and *minor* groups.

Table 10: Parameters of fitted Multi-type Interaction (MT) models.

| | Major | Minor | AIC | No. of parameters |
|---|---|---|---|---|
| | All nest sites | | | |
| **Major** | 1.1543 | 1.1910 | 13786.1 | 38 |
| **Minor** | 1.1910 | 1.1624 | | |
| | Wet season | | | |
| **Major** | 1.1871 | 1.3281 | 8429.041 | 33 |
| **Minor** | 1.3281 | 1.2207 | | |
| | Dry season | | | |
| **Major** | 1.0253 | 1.0244 | 6275.376 | 31 |
| **Minor** | 1.0244 | 1.0370 | | |

*Shaded areas highlight interaction terms (gamma) between nest site categories.

The bivariate higher-order interaction models portrayed an improvement over the bivariate IPP models fitted to the data. In all cases, gamma is greater than 1, suggesting attraction between nest site of the *Major* group and those of the *Minor* group. For the wet season nest site category, the AIC value was slightly less than that obtained from the IPP model, and the interaction parameter was greater than 1. This shows that higher-order interaction combined with covariate effect can better estimate an intensity function for this nest site category than covariate effect alone. Inhomogeneous cross bivariate *K functions* used for goodness-of-fit tests also showed that these models can be adequate to explain higher-order interaction between the two groups of gorillas in the sanctuary (Figure 17).



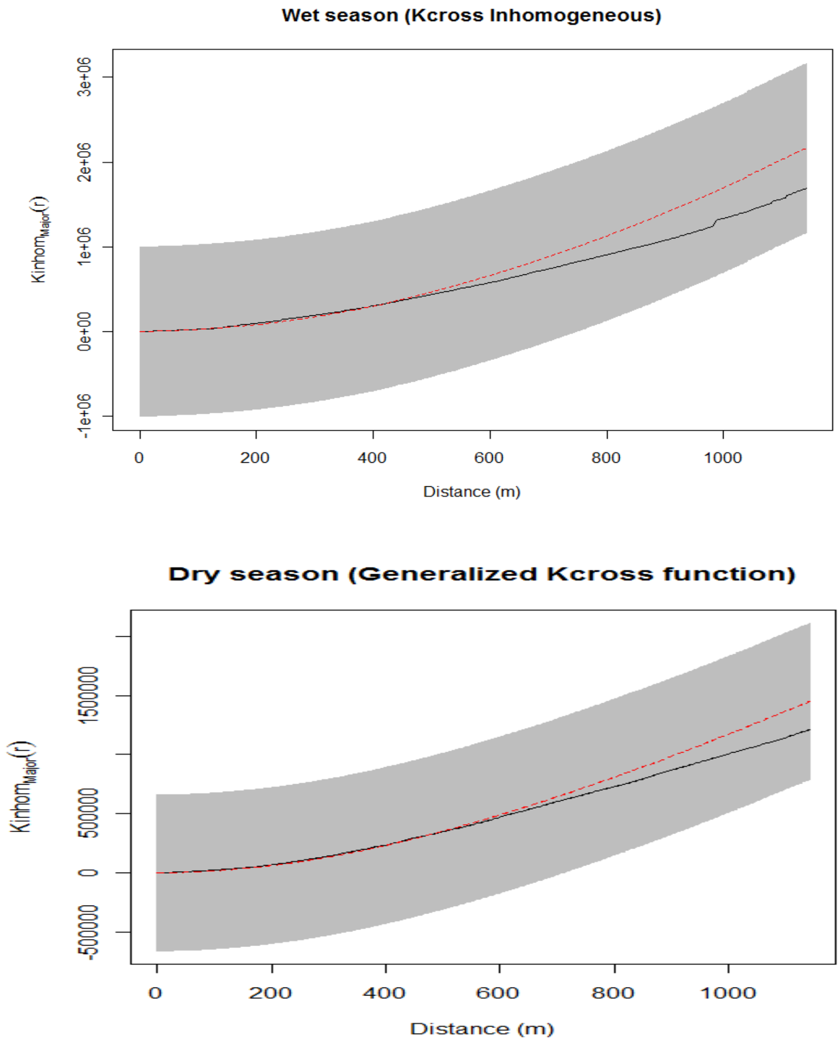



Figure 17: Goodness-of-fit plots for higher-order bivariate interaction models. The black lines represent the empirical inhomogeneous K functions while the grey bands represent envelopes computed from 99 simulations of the fitted models.

Despite the fact that the goodness-of-fit test and the interaction parameter (gamma) shows some attraction between nest sites of the two gorilla groups, it should again be noted here that the higher-order bivariate model implemented here is the Strauss process which, for reasons stated in the preceding chapter, cannot be completely trusted as the best model for a cluster process.

## CHAPTER 5: DISCUSSION, RECOMMENDATIONS AND CONCLUSION.

### 5.1 Discussion.

#### 5.1.1 Model fitting and selection.

Various models were fitted to the nest site data with the aim of obtaining models that can best constitute an intensity function for nest site distribution. The breakdown of the dataset into seasons provided the opportunity to obtain intensity functions for the different seasons and to verify differences in covariate effect during seasons. A breakdown into the two gorilla groups ranging in the sanctuary, the *major* and *minor* groups also provided a means of verifying differences that might come as a result of group size. From all the fitted models, the univariate point process models demonstrated a better fit to the dataset than bivariate models. This is illustrated by the AIC values obtained for the different model categories, as shown on Figure 18.

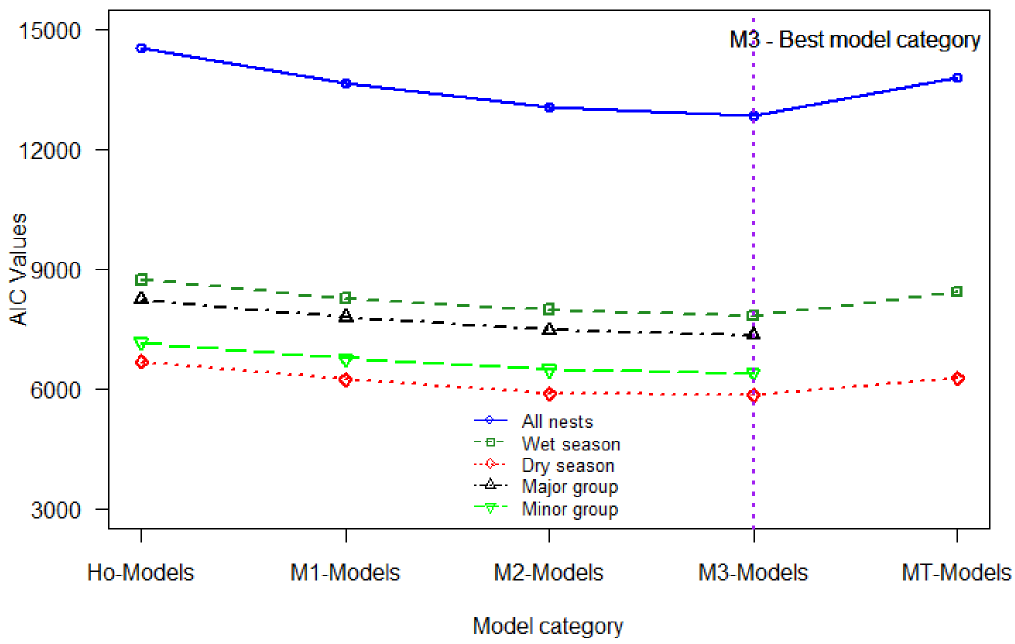



Figure 18: Summary plot of AIC values obtained for different models for each point pattern. Model categories on x-axis are: *Ho-Models* = Stationary model (univariate), *M1-Models* = inhomogeneous Poisson model with covariates only, *M2-Models* = inhomogeneous Poisson models with covariates and Cartesian coordinates, *M3-Models* = Combined model with covariate effect and Inter-point Interaction, and *MT-Models* = Multitype (bivariate) models with Inter-type interaction.

The AIC values for the models showed that M3-Models were the best models for describing the data. We therefore focus most of our discussion on the coefficients obtained from this category of models (Covariate effect and Inter-point interaction). It therefore indicates that gorilla nest site distribution in the sanctuary does not follow a Poisson process, but can be better explained by both covariates and interaction between points.

### 5.1.2 Interaction between nest sites.

The values of the interaction parameter eta obtained from the Area-Interaction model are much greater than one ($\eta >> 1$, Table 6), suggesting high attraction between nest site locations and creating a clustered process. CR gorillas in the sanctuary certainly prefer to locate nests where they have constructed nests before, and they have hotspots for nest site location. The predicted trends plotted from the fitted models (Figure 13) suggest that not much of the sanctuary may be used by the gorillas for nesting. Much less space may be available for gorilla nest site construction in the dry than in the wet season. However, the *minor* gorilla group also seems to find more conducive (high density) areas for nest site location in the sanctuary than the *major* group. This suggests a negative effect of group size on nest site distribution such that larger groups may have much limited space for nest site construction. In all cases, the southern-most parts of the sanctuary seem to present many disadvantages for nest site location, while intensity increases with increasing distance towards the central parts of the sanctuary. A view of the sanctuary from above (such as in Figure 19) may suggest the existence of a luxuriant forest, and may lead one to thinking there is much space for gorilla ranging. But our model results show that even though it may look all fancy and luxuriant, the interrelationship between factors, both natural and anthropogenic may result in very little space available for nest construction by the gorillas.

Figure 19: A view of the Kagwene Gorilla Sanctuary from above
(© Neba, 2008).

Although the Strauss models cannot be relied upon entirely, the results show that there is quite an attraction between the *minor* and *major* groups in the sanctuary ($\gamma_{major,\ minor} > 1$). It might be obvious enough, considering the limited space available for utilisation by the two groups. Each group simply may not be able to find a different location each time, and therefore attraction may be attributed to competition for resources.

### 5.1.3 Effect of covariates.

Before April 2008, the Kagwene Mountains were not yet officially a sanctuary. A significant group of gorillas had been identified there, but it was still a process to declare the place an official protected area. Since the creation of the sanctuary, it was envisaged that soon enough, human influence in the area will be significantly reduced, and thanks to the Cameroonian government and the Wildlife Conservation Society – TMLP, this is being achieved. Therefore, it is necessary to seek an understanding of the ecological behaviour of the gorillas in their natural habitat without man's intervension. This was a motivation why in selecting covariates for this study, we tried to limit them as much as we could to the natural environment. The results of the models have demonstrated that, even without human intervension, some natural factors still limit the gorillas' use of space. An earlier study carried out in the sanctuary by De Vere *et al* (2010) highlights the influence of anthropogenic factors on gorilla nest site location. Our results do not go to refute the findings of their study, but to complement them, and to further make predictions as to what areas of the sanctuary might be obvious nest site locations. This will be very important for conservation practice since, based on the results, priority areas can be carved out within the sanctuary for management.

The coefficients of the final model estimated for each environmental covariate show how the covariates affect nest site density in the sanctuary. These coefficients are displayed on Table 7. Covariates with positive coefficients have a positive effect on nest site density (attract nest site location), while variables with negative coefficients have negative contributions on nest site density (repel nest site location), and hence on nest site occurrence probability. The degree to which each variable contributes to log-intensity can also be judged from the value of the coefficient, with higher coefficients showing a higher positive or negative effect, as the case may be. The models were fitted as log-quadratic regressions of intensity, and each intensity is a product of several multiplicative components, each component representing the contribution of a predictor variable or interaction between points.

For all point pattern categories, nest site intensity gets lower with increasing elevation. This can be attributed to the habitat requirements of gorillas. The average elevation of all known CR gorilla localities measures 776m, and the Kagwene sanctuary is noted as being the highest point, with elevation measuring above 2000m (Bergl 2006). In fact, CR gorillas are classified as a subspecies of Lowland (Western) Gorillas (IUCN 2005; Oates *et al.* 2007).

Although higher altitudes provide a montane forest with more herbaceous vegetation, they are also associated with lower temperatures and increased exposure to climatic threats such as violent winds. Mid-elevation (sub-montane) forests may provide a much better pull to nest site construction due to rich undergrowth and less exposure. Therefore gorilla ranging in the sanctuary is expected to decrease with increasing altitude, as shown by the models. The final models show that a one meter increase in elevation is expected to cause log-intensity decrease by 0.0011 for all nest sites (aggregated points), 0.0012 in the wet season, 0.0062 in the dry season, 0.0028 for the Major gorilla group and 0.0029 for the Minor gorilla group, when all other factors are held constant. The effect of elevation is stronger in the dry season than wet season (which can be attributed to drier conditions at higher elevations probably presenting scanty vegetation), but there is an almost equal effect on both the Minor and Major groups.

Similarly, a one degree increase on slope causes an increase in log-intensity by 0.046 (all nest sites), 0.068 in the wet season, 0.054 in the dry season, 0.035 for Major gorilla group and 0.061 for Minor gorilla group. This confirms previous findings that Cross River Gorillas construct many ground nests on precipitous slopes (Wiseman 2008) and that they live in difficult terrain (Bergl 2006; Oates *et al.* 2007; Sunderland-Groves 2008). Levels of categorical variables such as vegetation type, slope position, heat index and aspect can be ranked in terms of their effect on log-intensity, based on their coefficients. Table 11 shows the ranking of these factors in terms of nest site occurrence probability.

Table 11: Ranking of categorical factor levels according to their effect on nest site distribution.

| **Factor** | **All nest sites** |
|---|---|
| **Vegetation type** | Transition > Secondary Forest > Colonizing forest > Primary forest* > Grassland* |
| **Aspect** | E > SE > W > NE > S > SW > NW* > N** |
| **Slope position** | Upper slope > Midslope > Ridge > Flat* > Toe slope* > Valley** |
| **Heat index** | Cool* > Warm* > Coolest** |
| | **Wet season** |
| **Vegetation type** | Transition > Secondary forest > Colonizing forest > Primary forest* > Grassland* |
| **Aspect** | E > NE > SE > W > NW > S* > SW* > N** |
| | **Dry Season** |
| **Vegetation type** | Colonizing forest* > Primary forest* > Grassland* > secondary forest* > Transition* |
| **Aspect** | SW > E > S > SE > NE > W > NW* > N** |
| | **Major group** |
| **Vegetation type** | Transition > Secondary forest > Colonizing forest > Primary forest* > Grassland* |
| **Aspect** | E > NE > SW > W > SE > NW > S* > N** |
| | **Minor Group** |
| **Vegetation type** | Colonizing forest > Transition* > Secondary forest* > Primary forest* > Grassland* |
| **Aspect** | E > SE > SW > S > SE > W > NE > NW > N** |

*Factor level exhibits a negative effect, **Factor level is absent (no effect)

According to Wiseman (2008), slope aspect did not show any significant effect on gorilla nest site distribution in the Kagwene Sanctuary. However, Wiseman recommended further analysis to verify the effect of aspect when it interacts with other factors such as slope gradient. The present analysis actually reveals that when we consider the interaction of aspect with other factors such as vegetation type, elevation, slope gradient etc, it surely creates a significant effect on nest site distribution. It should be noted that we consider the effects of the final selected variables as significant because the generalized *K function* fell within the upper and lower bounds of the simulated envelopes at all distances. Unfortunately, this cannot be further expressed in the form of any *p-value*s because no statistical theory currently supports this for non-Poisson processes (Baddeley and Turner 2006). For all nest sites (aggregated nest sites), all seasons and both Major and Minor groups, Eastern slopes tend to attract gorilla nest sites, while North-facing slopes were eliminated in all models. Eastern slopes have less exposure to sunshine and warmth and usually contain more moisture than Western slopes. This might have an effect on plant density with more herbal plants found on eastern slopes that can be used as nest-building materials or food. Also, the higher moisture on eastern slopes would, in the dry season, limit the spread of fire, creating a better ground for gorilla nesting.

Nest site density in the sanctuary is expected to change with change in vegetation type. Transition vegetation creates a pull effect on gorilla nest sites. The transition zone constitutes a unique vegetation community at the interface of grassland and montane forest, usually comprising of large herbs, bracken fern and woody shrubs (Sunderland *et al.* 2003). Common plant species found in this zone usually include *Aframomum pilosum, Aframomum arundinaceum, Brilliantasia lamium, Pteridium aquilinum, Lobelia columnaris*. Most of these species (especially the Zingiberaceae) are valuable food materials for CR gorillas in the KGS. This therefore explains why it would exert a pull to gorilla nest sites. It should be noted here that it does not necessarily mean that the most nest sites are constructed in transition vegetation, but that nest sites are more likely to occur closer to the transition zone than further away from it. Therefore intensity is expected to drop with increasing distance away from this zone. However in the dry season, all vegetation types portray a negative effect on log-intensity. The transition zone becomes very repellent probably because of the phonological characteristics of the plants that constitute this zone. Plants such as *Aframomum pilosum,* and *Aframomum arundinaceum* hardly bear fruit in this season (and so are not valuable food sources in this season), and the bracken fern (*Pteridium aquilinum*) dries up making the area so prone to bushfires in this season (Neba 2008). Gorillas in the

Kagwene sanctuary construct more ground nests in the dry than rainy season (Wiseman 2008) and nest heights of 0.1m and 0.5m are commonly observed in the dry season (Sunderland-Groves 2008). Therefore, while log-intensity is expected to decrease drastically in transition zones in the dry season, colonizing forests and primary forests do not repel nest site construction as much because of the presence of mixed undergrowth and shorter trees which provide adequate materials for construction of ground nests by gorillas. The gorillas are also known to feed more on of herbs like Acanthaceae during this season, in the absence of fruits.

### 5.2 Concluding remarks.

In this project, we have demonstrated that with the use of computational statistical tools, it is possible to study the ecological behaviour of wildlife species. The models fitted here have yielded information on the effect of selected environmental variables on gorilla nest site selection. They have also gone a long way to show that not only are gorilla nest site preferences affected by these variables, but there is an attractive interaction between nest sites. Therefore, there is a tendency of gorillas locating future nests where they have located nests before. Valuable ‘hotspots’ or ‘hotbeds’ can actually be identified for nest location, and such areas might be prioritized in management planning. It is however important that beyond the factors selected and used in the present models, more factors can be included to make conclusions more exhaustive, especially in verifying the combined effect of natural and anthropogenic factors.

This study was designed to answer specific questions about nest site distribution, and the resulting models have actually provided valuable answers to most of them. They tell us that nest site distribution is not random, and do not follow a stationaly (isotropic) distribution, but follows a clustered pattern where there is the likelihood of finding high nest site density in particular areas of the sanctuary than in others. The final models (M3-models) also show the effect of different environmental variables on nest site distribution, suggesting that while some factors attract nest site location, others repel and yet, some others do not have any significant effect when when an interplay of a combination of factors is considered. However, although these factors are said to affect nest site location, nest site distribution does not follow a Poisson process, but there is a higher-order interaction between nest sites. The models therefore have given answers to many of the questions that this project sought to answer, with the exception of the interaction between nest sites of the two gorilla groups. This is a software limitation to this study, given that only the Strauss process could be implemented. However unconvincing the results from the Strauss process are, they show that there is equally an attraction between nest sites of the Major and Minor groups.

### 5.3 Directions for further analysis.

This is a baseline study of this kind. The ecology of CR gorillas has been studied and models done have implemented more classical statistical methods. From the literature that was consulted during the study, this would be the first time CR gorilla ecology is studied through spatial statistics, and by utilizing techniques from the growing field of spatial ecological modelling. We therefore expect that further analysis can include a wider range of factors into models to yield more complete conclusions. In fact, the inclusion of Cartesian coordinates to the final models did illustrate that there are still other factor, besides the ones chosen for this study that contribute to provide an explanation for CR gorilla nest site selection in the Kagwene sanctuary. It is therefore highly recommended that further analysis includes a broader range of factors as they may be available. Also, the factors selected for the current models were intentionally limited to the natural environment. It would be very important to include anthropogenic factors for further analysis.

This project was limited by the fact that the main `R` software package used for the study (`spatstat`) is still under development (despite the fact that it has one of the highest number of built-in functions of all `R` packages) and certain models cannot be run at the moment. For instance, more recommended higher-order models such as the Geyer saturation and Area-Interaction models are not yet implemented for multi-type point patterns. Also, it would be interesting to create continuous marks for the data such that each nest site is not only marked by the group type (*major* or *minor group*), but by the actual number of individual gorillas found in the group. This would give a clearer conclusion on the effect of group size. Currently, this cannot be done within the limits of the analysis software package.

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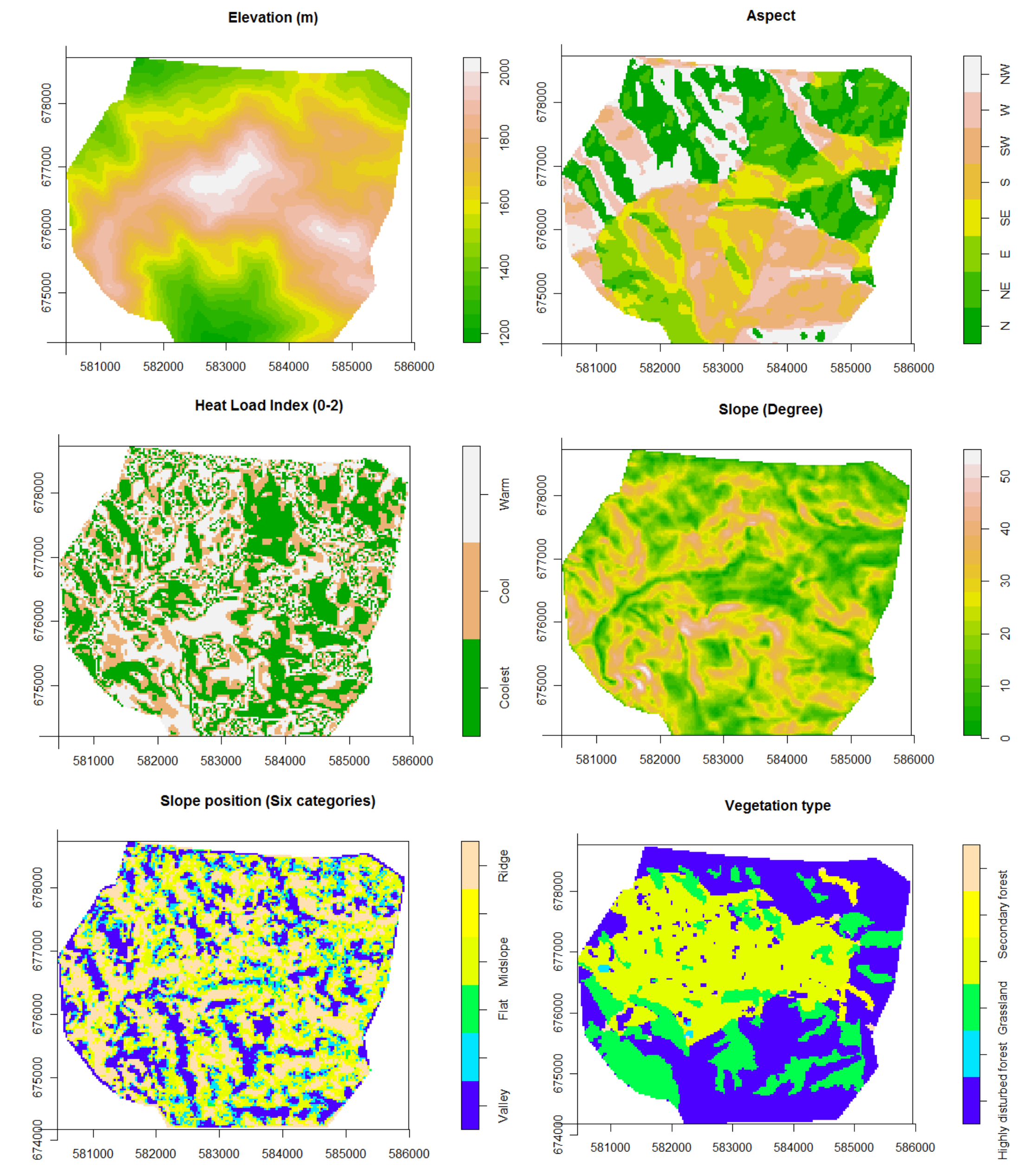
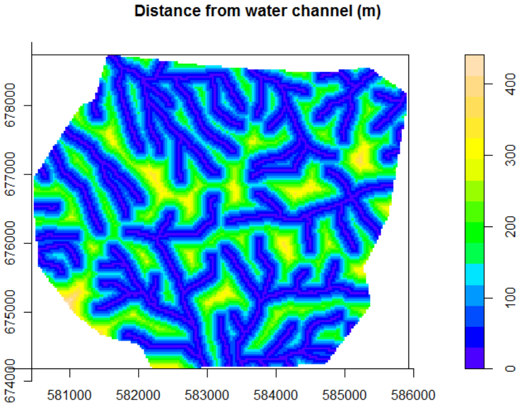
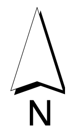
# APPENDICES

## Appendix A: Environmental covariates.




Projected Coordinate System: WGS_1984_UTM_Zone_32N
Projection: Transverse_Mercator
Geographic Coordinate System: GCS_WGS_1984.
Datum: D_WGS_1984

## Appendix B: Quadrat count statistics for different nest site patterns.

**Table 12: Quadrat test of CSR for different nest site.**

| Factor | Factor level | All Nest Sites Expected | All Nest Sites Observed | Wet season Expected | Wet season Observed | Dry season Expected | Dry season Observed | Major group Expected | Major group Observed | Minor group Expected | Minor group Observed |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Elevation (meters) | 1170-1527 | 160.6 | 62 | 92.1 | 50 | 68.8 | 12 | 86.3 | 34 | 74.3 | 28 |
| | 1527-1674 | 159.5 | 138 | 91.4 | 99 | 68.3 | 40 | 85.7 | 75 | 73.8 | 63 |
| | 1674-1813 | 160.6 | 107 | 92.1 | 57 | 68.8 | 50 | 86.3 | 61 | 74.3 | 46 |
| | 1813-2046 | 159.3 | 333 | 91.4 | 161 | 68.2 | 172 | 85.6 | 174 | 73.7 | 159 |
| | ***Chi Square ($\chi^2$)*** | ***$\chi^2$ = 270.686 p = 2.192180e-58*** | | ***$\chi^2$ = 86.3369 p = 1.340194e-18*** | | ***$\chi^2$ = 221.6341 p = 8.901864e-48*** | | ***$\chi^2$ = 131.6851 p = 2.343714e-28*** | | ***$\chi^2$ = 139.963 p = 3.849817e-30*** | |
| Aspect | North | 119.1 | 160 | 68.3 | 99 | 51 | 62 | 64 | 87 | 55.1 | 73 |
| | Northeast | 83.83 | 82 | 58 | 55 | 35.9 | 27 | 45 | 48 | 38.8 | 34 |
| | East | 62 | 29 | 35.6 | 19 | 26.6 | 10 | 33.9 | 19 | 28.7 | 10 |
| | Southeast | 50.9 | 73 | 29.2 | 38 | 21.8 | 35 | 27.4 | 33 | 23.5 | 40 |
| | South | 84.7 | 46 | 48.6 | 17 | 36.3 | 29 | 45.5 | 23 | 39.2 | 23 |
| | Southwest | 89 | 49 | 51 | 18 | 38.1 | 31 | 47.8 | 28 | 41.2 | 21 |
| | West | 66.1 | 80 | 37.9 | 56 | 28.3 | 24 | 35.5 | 43 | 30.6 | 37 |
| | Northwest | 84.4 | 121 | 48.4 | 65 | 36.1 | 56 | 45.3 | 63 | 39 | 58 |
| | ***Chi Square ($\chi^2$)*** | ***$\chi^2$ = 95.7691 p = 8.048172e-18*** | | ***$\chi^2$ = 81.4471 p = 6.98e-15*** | | ***$\chi^2$ = 37.2806 p = 4.150141e-06*** | | ***$\chi^2$ = 43.6065 p = 2.547e-07*** | | ***$\chi^2$ = 57.229 p = 5.383e-10*** | |
| Slope position | Valley | 140.8 | 100 | 80.7 | 61 | 60.3 | 39 | 75.7 | 49 | 65.1 | 51 |
| | Toe slope | 88.4 | 80 | 50.7 | 48 | 37.9 | 33 | 47.5 | 39 | 40.9 | 41 |
| | Flat | 3 | 2 | 17 | 1 | 13 | 1 | 16 | 1 | 14 | 1 |
| | Mid slope | 184.9 | 205 | 106 | 118 | 79.2 | 87 | 99.4 | 116 | 85.5 | 89 |
| | Upper slope | 70.2 | 81 | 40.2 | 40 | 30 | 41 | 37.7 | 42 | 32.5 | 39 |
| | Ridge | 152.7 | 172 | 87.6 | 99 | 65.4 | 73 | 82.1 | 97 | 70.6 | 75 |
| | ***Chi Square ($\chi^2$)*** | ***$\chi^2$ = 19.2165 p = 0.001752*** | | ***$\chi^2$ = 8.1007 p = 0.1508*** | | ***$\chi^2$ = 13.8414 p = 0.01665*** | | ***$\chi^2$ = 17.1222 p = 0.004274*** | | ***$\chi^2$ = 4.8903 p = 0.4294*** | |
| Heat Index | Coolest | 249.5 | 260 | 143.1 | 155 | 106.8 | 105 | 134.1 | 145 | 115.4 | 115 |
| | Cool | 175.2 | 175 | 100.5 | 99 | 75 | 76 | 94.2 | 90 | 81 | 85 |
| | Warm | 215.3 | 205 | 123.4 | 113 | 92.2 | 93 | 115.7 | 109 | 99.6 | 96 |
| | ***Chi Square ($\chi^2$)*** | ***$\chi^2$ = 0.9286, p = 0.6286*** | | ***$\chi^2$ = 1.8958 p =0.3879*** | | ***$\chi^2$ = 0.0519 p = 0.9744*** | | ***$\chi^2$ = 1.4563 p = 0.4828*** | | ***$\chi^2$ = 0.3219 p = 0.8513*** | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Vegetation | Highly disturbed forest | 281.8 | 97 | 161.6 | 47 | 120.7 | 51 | 151.5 | 54 | 130.4 | 43 |
| | Colonizing forest | 14 | 3 | 8 | 3 | 6 | 0 | 8 | 2 | 6 | 1 |
| | Grassland | 135.7 | 19 | 77.8 | 13 | 58.1 | 6 | 72.9 | 11 | 62.8 | 8 |
| | Primary forest | 210.1 | 518 | 120.5 | 301 | 90 | 217 | 112.9 | 274 | 97.2 | 244 |
| | Secondary forest | 85 | 2 | 49 | 2 | 36 | 0 | 46 | 2 | 3.9 | 0 |
| | Transition | 24 | 1 | 14 | 1 | 1 | 0 | 13 | 1 | 11 | 0 |
| | ***Chi Square ($\chi^2$)*** | ***$\chi^2$ = 680.2936, p = 8.951409e-145*** | | ***$\chi^2$ = 413.4637 p = 3.716402e-87*** | | ***$\chi^2$ = 271.6137 p = 1.259991e-56*** | | ***$\chi^2$ = 348.5728 p = 3.551127e-73*** | | ***$\chi^2$ = 333.3546 p = 6.699762e-70*** | |
| Water distance (meters) | 0 - 43.52 | 125.7 | 89 | 72.2 | 57 | 53.6 | 32 | 67.8 | 47 | 57.9 | 42 |
| | 43.5 - 92.3 | 144.5 | 135 | 83.1 | 85 | 61.7 | 51 | 77.9 | 71 | 66.6 | 64 |
| | 92.3 - 153.8 | 163.8 | 147 | 94.1 | 84 | 69.9 | 63 | 88.3 | 79 | 75.5 | 68 |
| | 153.8 - 440.5 | 154 | 217 | 88.5 | 112 | 65.7 | 105 | 83 | 120 | 71 | 97 |
| | ***Chi Square ($\chi^2$)*** | ***$\chi^2$ = 38.8252, p = 1.89e-08*** | | ***$\chi^2$ = 10.5805 p = 0.01422*** | | ***$\chi^2$ = 34.7225 p = 1.394e-07*** | | ***$\chi^2$ = 24.4192 p = 2.042e-05*** | | ***$\chi^2$ = 14.7638 p = 0.00203*** | |

**Appendix C: Intensity functions for final models (M3 Models).**

| Point pattern category | Intensity formula |
|---|---|
| All nest sites (aggregated) | $\lambda_\theta(u,x) = exp$(-583303.5 - 0.001($C_1$) + 0.0000005($C_1$)² + 0.183($C_2$: *northeast*) + 0.537($C_2$: *east*) + 0.439($C_2$: *southeast*) + 0.154($C_2$: *south*) + 0.097($C_2$: *southwest*) + 0.287($C_2$: *west*) - 0.076($C_2$: *northwest*) - 0.085($C_3$: *cool*) - 0.094($C_3$: *warm*) - 0.026($C_4$: *toe slope*) - 0.006($C_4$: *flat*) + 0.146($C_4$: *mid slope*) + 0.183($C_4$: *upper slope*) + 0.135($C_4$: *ridge*) + 0.078($C_5$: *colonizing forest*) - 1.142($C_5$: *grassland*) - 0.573($C_5$: *primary forest*) + 0.429($C_5$: *secondary forest*) + 1.763($C_5$: *transition vegetation*) + 0.046($C_6$) - 0.0009($C_6$)² + 3.436) |
| Wet season nest sites | $\lambda_\theta(u,x) = exp$(-578279.2- 0.001($C_1$) + 0.0000005($C_1$)² + 0.393 ($C_2$: *northeast*) + 0.821 ($C_2$: *east*) + 0.378 ($C_2$: *southeast*) - 0.046 ($C_2$: *south*) -0.062 ($C_2$: *southwest*) + 0.244 ($C_2$: *west*) + 0.233 ($C_2$: *northwest*) + 0.661 ($C_5$: *colonizing forest*) - 0.986 ($C_5$: *grassland*) - 0.213 ($C_5$: *primary forest*) + 0.782 ($C_5$: *secondary forest*) + 1.738 ($C_5$: *transition vegetation*) + 0.068 ($C_6$) -0.001 ($C_6$)² + 0.002 ($C_7$) + -0.0000009 ($C_7$)² + 2.911) |
| Dry season | $\lambda_\theta(u,x) = exp$(-1198242 - 0.006 ($C_1$) + 0.000002 ($C_1$)² + 0.189 ($C_2$: *northeast*) + 0.533 ($C_2$: *east*) + 0.308 ($C_2$: *southeast*) + 0.460 ($C_2$: *south*) + 0.762 ($C_2$: *southwest*) + 0.072 ($C_2$: *west*) - 0.00002 ($C_2$: *northwest*) - 0.133 ($C_5$: *colonizing forest*) -1.619 ($C_5$: *grassland*) - 0.914 ($C_5$: *primary forest*) - 6.889 ($C_5$: *secondary forest*) -7.925 ($C_5$: *transition vegetation*) + 0.054 ($C_6$) - 0.001 ($C_6$)² + 8.118) |
| Major group | $\lambda_\theta(u,x) = exp$(-797904.7- 0.003 ($C_1$) + 0.000001 ($C_1$)² + 0.279 ($C_2$: *northeast*) + 0.759 ($C_2$: *east*) + 0.056 ($C_2$: *southeast*) - 0.014 ($C_2$: *south*) + 0.199 ($C_2$: *southwest*) + 0.090 ($C_2$: *west*) + 0.025 ($C_2$: *northwest*) + 0.520 ($C_5$: *colonizing forest*) -1.037 ($C_5$: *grassland*) - 0.408 ($C_5$: *primary forest*) +1.057 ($C_5$: *secondary forest*) +2.147 ($C_5$: *transition vegetation*) + 0.035 ($C_6$) -0.0007 ($C_6$)² + 2.545 |
| Minor group | $\lambda_\theta(u,x) = exp$(-777617.6 - 0.003 ($C_1$) + 0.000001 ($C_1$)² + 0.271 ($C_2$: *northeast*) + 0.716 ($C_2$: *east*) + 0.614 ($C_2$: *southeast*) + 0.364 ($C_2$: *south*) + 0.513 ($C_2$: *southwest*) + 0.314 ($C_2$: *west*) + 0.108 ($C_2$: *northwest*) +1.080 ($C_5$: *colonizing forest*) -1.115 ($C_5$: *grassland*) -0.429 ($C_5$: *primary forest*) - 0.128 ($C_5$: *secondary forest*) - 0.123 ($C_5$: *transition vegetation*) + 0.061 ($C_6$) -0.001 ($C_6$)² + 2.648) |

$C_1$, $C_2$, $C_3$…$C_7$ represent spatial covariates: elevation, aspect, heat index, slope position, vegetation, slope degree and distance from water respectively.

## Appendix D: R script written for analysis.

```
#.........................................................................
# Title:            Neba_MSc_Thesis.R
#
# Author:           Neba, Funwi-Gabga
#
# Date:             February 2011
#
# Topic:            Spatial point pattern analysis of Gorilla nest
#                   sites in the Kagwene Sanctuary, Cameroon.
#                   towards understanding the nesting behaviour
#                   of a critically endangered subspecies.
#
# Covariates:       elevation, slope degree, slope position,
#                   vegetation type, distance from water, heat load
#                   index, aspect
#.........................................................................


####
# Set working directory and load workspace
setwd("D:\\My thesis gis\\GIS final\\all_data_for_R")
load("E:\\My thesis gis\\GIS final\\all_data_for_R\\Neba_MSc_Thesis.R")

# Load required libraries in R
packages<-function(){
       library(sp)
       library(rgdal)
       library(maptools)
       library(spatstat)
       library(combinat)
       library(adehabitat)
      }
packages()

# Read covariates into R and convert to class "im" for spatstat
# Elevation
elevation<-readGDAL("elevation.asc")
names(elevation)[1]<-"Elevation"
proj4string(elevation)=CRS("+init=epsg:22832") # This is UTM zone 32N (Douala)
elevation.im<-as.im(elevation)
# Aspect
aspect<-readGDAL("aspect.asc")
names(aspect)[1]<-"Aspect"
proj4string(aspect)=CRS("+init=epsg:22832") # This is UTM zone 32N (Douala)
aspect.im<-as.im(aspect)
aspect.factor<-cut(aspect.im, breaks=8,
       labels=c("N","NE","E","SE","S","SW","W","NW"))
# Heat Load
heat.index<-readGDAL("heat_index.asc")
names(heat.index)[1]<-"Heat_Index"
proj4string(heat.index)=CRS("+init=epsg:22832") # This is UTM zone 32N (Douala)
heat.index.im<-as.im(heat.index)
heat.index.factor<-cut(heat.index.im, breaks=3,
       labels=c("Coolest","Cool","Warm"))
# Degree Slope
slope<-readGDAL("slope_degree.asc")
names(slope)[1]<-"Percent_Slope"
proj4string(slope)=CRS("+init=epsg:22832") # This is UTM zone 32N (Douala)
slope.im<-as.im(slope)
# Slope Position
slope.position<-readGDAL("slope_position.asc")
names(slope.position)[1]<-"Slope_Position"
proj4string(slope.position)=CRS("+init=epsg:22832") # This is UTM zone 32N (Douala)
slope.position.im<-as.im(slope.position)
slope.position.factor<-cut(slope.position.im, breaks=6,
```

```
       labels=c("Valley","Toe slope","Flat","Midslope","Upper slope","Ridge"))
# Vegetation type
vegetation<-readGDAL("vegetation.asc")
names(vegetation)[1]<-"Vegetation"
proj4string(vegetation)=CRS("+init=epsg:22832") # This is UTM zone 32N (Douala)
vegetation.im<-as.im(vegetation)
vegetation.factor<-cut(vegetation.im, breaks=6,
       labels=c("Highly disturbed forest", "Colonizing forest",
       "Grassland", "Primary forest", "Secondary forest", "Transition"))
# Distance from water
water.distance<-readGDAL("water_distance.asc")
names(water.distance)[1]<-"Distance"
proj4string(water.distance)=CRS("+init=epsg:22832") # This is UTM zone 32N (Douala)
water.distance.im<-as.im(water.distance)

# Shorten covariate names for model fitting
elevation.im->el
aspect.factor->asp
slope.im->sl
slope.position.factor->slp
heat.index.factor->hi
water.distance.im->wd
vegetation.factor->v

# Create tessellation of covariates for quadrat count
elevation.quantiles<-quantile(elevation.im, probs=(0:4)/4)
elevation.cut<-cut(elevation.im, breaks=elevation.quantiles, labels=1:4)
elevation.tess<-tess(image=elevation.cut)
aspect.tess<-tess(image=aspect.factor)
slope.position.tess<-tess(image=slope.position.factor)
heat.index.tess<-tess(image=heat.index.factor)
vegetation.tess<-tess(image=vegetation.factor)
water.distance.quantiles<-quantile(water.distance.im, probs=(0:4)/4)
water.distance.cut<-cut(water.distance.im, breaks=water.distance.quantiles,
       labels=1:4)
water.distance.tess<-tess(image=water.distance.cut)

# Read study area polygon into R and convert to window for spatstat
kgs<-readShapePoly("Kagwene.shp")
proj4string(slope.position)=CRS("+init=epsg:22832")
kgs.w<-as(kgs, "owin")

# Read point data into R and convert into spatstat class "ppp"
# All nests
locs<-read.csv("Neba_nests_final.csv", h=T,sep=",")
CoorXY<-locs[,3:4]
coordinates(locs)<-CoorXY
x<-locs$X
y<-locs$Y
group<-factor(locs$group)

# rainy season nests
locs.rainy<-read.csv("Neba_nests_rainy_season_final.csv", h=T, sep=",")
CoorXY.rainy<-locs.rainy[,3:4]
coordinates(locs.rainy)<-CoorXY.rainy
x.rainy<-locs.rainy$X
y.rainy<-locs.rainy$Y
group.rainy<-factor(locs.rainy$group)

# dry season nests
locs.dry<-read.csv("Neba_nests_dry_season_final.csv", h=T, sep=",")
CoorXY.dry<-locs.dry[,3:4]
coordinates(locs.dry)<-CoorXY.dry
x.dry<-locs.dry$X
y.dry<-locs.dry$Y
group.dry<-factor(locs.dry$group)
```

```
# Point patterns with no seasons
gorillas<-ppp(x, y, window=kgs.w, marks=group)
# check for duplicate points
any(duplicated(gorillas))
# If true, remove duplicated points
nests<-unique(gorillas) #Marked point pattern
nests.unmarked<-unmark(nests) #Unmarked point pattern
nests.split<-split(nests)
major<-nests.split$Major #Major group nests
minor<-nests.split$Minor #Minor group nests

# Point patterns with seasons
# Marked Rainy season ppp
gorillas.rainy<-ppp(x.rainy, y.rainy, window=kgs.w, marks=group.rainy)
any(duplicated(gorillas.rainy))  # this uses group size as marks
nests.rainy<-unique(gorillas.rainy)
# Unmarked rainy season
nests.rainy.unmarked<-unmark(nests.rainy)
# Marked Dry season ppp
gorillas.dry<-ppp(x.dry, y.dry, window=kgs.w, marks=group.dry)
any(duplicated(gorillas.dry))  # this uses group size as marks
nests.dry<-unique(gorillas.dry)
# Unmarked dry season
nests.dry.unmarked<-unmark(nests.dry)

# Plot all images to see
covariates<-function(){
	par(mfrow=c(2,4))
	plot(elevation.im, axes=T, col=terrain.colors(20), main="Elevation (m)")
	plot(aspect.factor, axes=T, col=terrain.colors(8), main="Aspect")
	plot(heat.index.factor, axes=T, col=terrain.colors(3), main="Heat Load
		Index (0-2)")
	plot(slope.im, axes=T, col=terrain.colors(20), main="Slope (Percent)")
	plot(slope.position.factor, axes=T, col=topo.colors(6), main="Slope
		position (Six categories)")
	plot(vegetation.factor, axes=T, col=topo.colors(6), main="Vegetation
		type")
	plot(water.distance.im, axes=T, col=topo.colors(15), main="Distance from
		water channel (m)")
	plot(nests, axes=T, pch=16, cex=0.5, main="Gorilla nest site locations")
}
covariates()
# end of data input
#######################################################

#First-order characteristics - Kernel smoothed intensity plots
plot(density(nests.unmarked), axes=F, col=topo.colors(20), font.lab=2, main="(a)
	All nest sites")
plot(nests.unmarked, pch=16, cex=0.45, add=T, col=2)
plot(density(nests.rainy.unmarked), axes=F, col=topo.colors(20), font.lab=2,
	main="(b) Wet season")
plot(nests.rainy.unmarked, pch=16, cex=0.45, add=T, col=2)
plot(density(nests.dry.unmarked), axes=F, col=topo.colors(20), font.lab=2,
	main="(c) Dry season")
plot(nests.dry.unmarked, pch=16, cex=0.45, add=T, col=2)
plot(density(major), axes=F, col=topo.colors(20), font.lab=2, main="(d) Major
	group")
plot(major, pch=16, cex=0.45, add=T, col=2)
plot(density(minor), axes=F, col=topo.colors(20), font.lab=2, main="(e) Minor
	group")
plot(minor, pch=16, cex=0.45, add=T, col=2)
# end first order
##################################

# Test for CSR
# a. Quadrat counting (Chi Square) test
# all nests
```

```
qc1<-quadrat.test(nests.unmarked, tess=elevation.tess)
qc2<-quadrat.test(nests.unmarked, tess=aspect.tess)
qc3<-quadrat.test(nests.unmarked, tess=heat.index.tess)
qc4<-quadrat.test(nests.unmarked, tess=slope.position.tess)
qc5<-quadrat.test(nests.unmarked, tess=water.distance.tess)
qc6<-quadrat.test(nests.unmarked, tess=vegetation.tess)
# Wet season nests
qc7<-quadrat.test(nests.rainy.unmarked, tess=elevation.tess)
qc8<-quadrat.test(nests.rainy.unmarked, tess=aspect.tess)
qc9<-quadrat.test(nests.rainy.unmarked, tess=heat.index.tess)
qc10<-quadrat.test(nests.rainy.unmarked, tess=slope.position.tess)
qc11<-quadrat.test(nests.rainy.unmarked, tess=water.distance.tess)
qc12<-quadrat.test(nests.rainy.unmarked, tess=vegetation.tess)
# Dry season
qc13<-quadrat.test(nests.dry.unmarked, tess=elevation.tess)
qc14<-quadrat.test(nests.dry.unmarked, tess=aspect.tess)
qc15<-quadrat.test(nests.dry.unmarked, tess=heat.index.tess)
qc16<-quadrat.test(nests.dry.unmarked, tess=slope.position.tess)
qc17<-quadrat.test(nests.dry.unmarked, tess=water.distance.tess)
qc18<-quadrat.test(nests.dry.unmarked, tess=vegetation.tess)
# Major group
qc19<-quadrat.test(major, tess=elevation.tess)
qc20<-quadrat.test(major, tess=aspect.tess)
qc21<-quadrat.test(major, tess=heat.index.tess)
qc22<-quadrat.test(major, tess=slope.position.tess)
qc23<-quadrat.test(major, tess=water.distance.tess)
qc24<-quadrat.test(major, tess=vegetation.tess)
# Minor group
qc25<-quadrat.test(minor, tess=elevation.tess)
qc26<-quadrat.test(minor, tess=aspect.tess)
qc27<-quadrat.test(minor, tess=heat.index.tess)
qc28<-quadrat.test(minor, tess=slope.position.tess)
qc29<-quadrat.test(minor, tess=water.distance.tess)
qc30<-quadrat.test(minor, tess=vegetation.tess)

# b. Summary functions (K and L).
plot(envelope(nests.unmarked, fun=Kest, nsim=99, global=T,control=list(expand=1),
       nrank=2), legend=F, main="All nests (K function)", xlab="Distance (m)")
plot(envelope(nests.unmarked, fun=Lest, nsim=99, control=list(expand=1), nrank=2),
       legend=F, main="All nests (L funtion)", xlab="Distance (m)")
plot(envelope(nests.rainy.unmarked, fun=Kest, global=T, nsim=99,
control=list(expand=1), global=T, nrank=2), legend=F, main="Wet season (K
       function)", xlab="Distance (m)")
plot(envelope(nests.rainy.unmarked, fun=Lest, nsim=99, control=list(expand=1),
       global=T, nrank=2), legend=F, main="Wet season (L function)", xlab="Distance
       (m)")
plot(envelope(nests.dry.unmarked, fun=Kest, nsim=99, control=list(expand=1),
       global=T, nrank=2), legend=F, main="Dry season (K function)", xlab="Distance
       (m)")
plot(envelope(nests.dry.unmarked, fun=Lest, nsim=99, control=list(expand=1),
       global=T, nrank=2), legend=F, main="Dry season (L function)", xlab="Distance
       (m)")
plot(envelope(major, fun=Kest, nsim=99, control=list(expand=1), global=T,
       nrank=2), legend=F, main="Major group (K function)", xlab="Distance (m)")
plot(envelope(major, Lest, nsim=99, control=list(expand=1), global=T, nrank=2),
       legend=F, main="Major group (L function)", xlab="Distance (m)")
plot(envelope(minor, Kest, nsim=99, control=list(expand=1), global=T, nrank=2),
       legend=F, main="Minor group (K function)", xlab="Distance (m)")
plot(envelope(minor, Lest, nsim=99, control=list(expand=1), global=T, nrank=2),
       legend=F, main="Minor group (L function)", xlab="Distance (m)")
# end of test for CSR
##############################

# Model fitting
# Homogeneous poisson models (stationary)
nests.unmarked.null<-ppm(nests.unmarked, ~1)
nests.dry.unmarked.null<-ppm(nests.dry.unmarked, ~1)
```

```
nests.rainy.unmarked.null<-ppm(nests.rainy.unmarked, ~1)
major.null<-ppm(major, ~1)
minor.null<-ppm(minor, ~1)

# Generate all possible combinations of covariates
library(combinat)
mycov<-c("el", "hi","v","asp","sl","slp","wd")
two.combs<-combn(mycov, 2)
three.combs<-combn(mycov, 2)
four.combs<-combn(mycov, 2)
five.combs<-combn(mycov, 2)
six.combs<-combn(mycov, 2)
seven.combs<-combn(mycov, 2)

####################3
# Model with spatial trend dependent on covariates (IPP).
all.nests.fit<-ppm(nests.unmarked, ~polynom(el, 2)+asp+polynom(sl, 2)+slp+hi+v,
       covariates=list(el=el, asp=asp, sl=sl, slp=slp, hi=hi, v=v))
rainy.fit<-ppm(nests.rainy.unmarked, ~polynom(el, 2)+asp+polynom(sl,
       2)+polynom(wd, 2)+v, covariates=list(el=el, asp=asp, sl=sl, wd=wd, v=v))
dry.fit<-ppm(nests.dry.unmarked, ~polynom(el, 2)+asp+polynom(sl, 2)+v,
       covariates=list(el=el, asp=asp, sl=sl, v=v))
major.fit<-ppm(major, ~polynom(el, 2)+asp+polynom(sl, 2)+v,
       covariates=list(el=el, asp=asp, sl=sl, v=v))
minor.fit<-ppm(minor, ~polynom(el, 2)+asp+polynom(sl, 2)+v,
       covariates=list(el=el, asp=asp, sl=sl, v=v))

# Model with spatial trend dependent on covariates and cartesian coordinates
all.nests.combined<-ppm(nests.unmarked, ~polynom(x,y,2)+polynom(el,
       2)+asp+polynom(sl, 2)+slp+hi+v, covariates=list(el=el, asp=asp, sl=sl,
       slp=slp, hi=hi, v=v))
rainy.combined<-ppm(nests.rainy.unmarked, ~polynom(x,y,2)+polynom(el,
       2)+asp+polynom(sl, 2)+polynom(wd, 2)+v, covariates=list(el=el, asp=asp,
       sl=sl, wd=wd, v=v))
dry.combined<-ppm(nests.dry.unmarked, ~polynom(x,y,2)+polynom(el,
       2)+asp+polynom(sl, 2)+v, covariates=list(el=el, asp=asp, sl=sl, v=v))
major.combined<-ppm(major, ~polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl, 2)+v,
       covariates=list(el=el, asp=asp, sl=sl, v=v))
minor.combined<-ppm(minor, ~polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl, 2)+v,
       covariates=list(el=el, asp=asp, sl=sl, v=v))

# Combined model with spatial trend (Cartesian coordinates and covariates) and
Interpoint interaction
# area-interaction model
# Estimating irregular parameters for interaction models
ip=data.frame(r=seq(100, 1150, by=115))
# All nests
fit.all.area.inter<-profilepl(ip, AreaInter,nests.unmarked,
       ~polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl, 2)+slp+hi+v,
       covariates=list(el=el, asp=asp, sl=sl, slp=slp, hi=hi, v=v), rbord=0.05)
AI.all<-fit.all.area.inter$fit #extracts the model from the equation
# Wet season
fit.rainy.area.inter<-profilepl(ip, AreaInter, nests.rainy.unmarked,
       ~polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl, 2)+polynom(wd, 2)+v,
       covariates=list(el=el, asp=asp, sl=sl, wd=wd, v=v), rbord=0.05)
AI.rainy<-fit.rainy.area.inter$fit #extracts the model from the equation
# Dry season
fit.dry.area.inter<-profilepl(ip, AreaInter, nests.dry.unmarked,
       ~polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl, 2)+v, covariates=list(el=el,
       asp=asp, sl=sl, v=v), rbord=0.05)
AI.dry<-fit.dry.area.inter$fit #extracts the model from the equation
# Major group
fit.major.area.inter<-profilepl(ip, AreaInter, major,
       ~polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl, 2)+v, covariates=list(el=el,
       asp=asp, sl=sl, v=v), rbord=0.05)
AI.major<-fit.major.area.inter$fit #extracts the model from the equation
```

```
# Minor group
fit.minor.area.inter<-profilepl(ip, AreaInter, minor,
       ~polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl, 2)+v, covariates=list(el=el,
       asp=asp, sl=sl, v=v), rbord=0.05)
AI.minor<-fit.minor.area.inter$fit #extracts the model from the equation

# Plot the profile log pseudolikelihoods to obtain (show) the irregular parameters.
par(mfrow=c(2,3))
plot(fit.all.area.inter,cex.main=1.6,cex.lab=2,lwd=2,xlab="Interaction radius
       (r)", ylab="log pseudolikelihood (logPL)", main="(a) All nest sites")
plot(fit.rainy.area.inter,cex.main=1.6,cex.lab=2,xlab="Interaction radius (r)",
       ylab="log pseudolikelihood (logPL)", lwd=2,main="(b) Wet season nest
       sites")
plot(fit.dry.area.inter,cex.main=1.6,cex.lab=1.5,xlab="Interaction radius (r)",
       ylab="log pseudolikelihood (logPL)", lwd=1.5,main="(c) Dry season nest
       sites")
plot(fit.major.area.inter,cex.main=1.6,cex.lab=1.5,xlab="Interaction radius
       (r)", ylab="log pseudolikelihood (logPL)", lwd=1.5,main="(d) Major group
       nest sites")
plot(fit.minor.area.inter,cex.main=1.6,cex.lab=1.5,xlab="Interaction radius
       (r)", ylab="log pseudolikelihood (logPL)", lwd=1.5,main="(e) Minor group
       nest sites")

# Inhomogeneous K functions from the fitted models
par(mfrow=c(1,3))
plot(envelope(AI.all, fun=Kinhom, global=T, nrank=2, nsim=99,
       control=list(expand=1)), legend=F, main="All nest sites", xlab="Distance
       (m)")
plot(envelope(AI.rainy, fun=Kinhom, global=T, nrank=2, nsim=99,
       control=list(expand=1)), legend=F, main="All nest sites", xlab="Distance
       (m)")
plot(envelope(AI.dry, fun=Kinhom, global=T, nrank=2, nsim=99,
       control=list(expand=1)), legend=F, main="All nest sites", xlab="Distance
       (m)")
plot(envelope(AI.major, fun=Kinhom, global=T, nrank=2, nsim=99,
       control=list(expand=1)), legend=F, main="All nest sites", xlab="Distance
       (m)")
plot(envelope(AI.minor, fun=Kinhom, global=T, nrank=2, nsim=99,
       control=list(expand=1)), legend=F, main="All nest sites", xlab="Distance
       (m)")

# model diagnostics
# lurking variable plots
# Covariates only (M1 models)
par(mfrow=c(2,3))
lurking(all.nests.fit, covariate=el, type="pearson", covname="Elevation
       (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="All nest sites and Elevation")
lurking(all.nests.fit, covariate=sl, type="pearson", covname="Slope
       degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="All nest sites and Slope")
lurking(rainy.fit, covariate=el, type="pearson", covname="Elevation
       (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Wet season nest sites and
       Elevation")
lurking(rainy.fit, covariate=sl, type="pearson", covname="Slope
       degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Wet season nest sites and
       Slope")
lurking(rainy.fit, covariate=wd, type="pearson", covname="Distance from water
       (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Wet season nest sites and
       Distance from water")
lurking(dry.fit, covariate=el, type="pearson", covname="Elevation
       (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Dry season nest sites and
       Elevation")
lurking(dry.fit, covariate=sl, type="pearson", covname="Slope
       degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Dry season nest sites and
       Slope")
lurking(major.fit, covariate=el, type="pearson", covname="Elevation
       (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Major group nest sites and
Elevation")
```

```
    lurking(major.fit, covariate=sl, type="pearson", covname="Slope
    degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Major group nest sites and
    Slope")
lurking(minor.fit, covariate=el, type="pearson", covname="Elevation
    (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Minor group nest sites and
    Elevation")
lurking(minor.fit, covariate=sl, type="pearson", covname="Slope
    degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Minor group nest sites and
    Elevation")


# Against Cartesian coordinates
par(mfrow=c(2,5))
diagnose.ppm(all.nests.fit, which = "x", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="All nest sites with X-Coords")
diagnose.ppm(all.nests.fit, which = "y", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="All nest sites with Y-Coords")
diagnose.ppm(rainy.fit, which = "x", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Wet season with X-Coords")
diagnose.ppm(rainy.fit, which = "y", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Wet season with Y-Coords")
diagnose.ppm(dry.fit, which = "x", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Dry season nest sites with X-
    Coords")
diagnose.ppm(dry.fit, which = "y", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Dry season nest sites with Y-
    Coords")
diagnose.ppm(major.fit, which = "x", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Major group nest sites with X-
    Coords")
diagnose.ppm(major.fit, which = "y", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Major group nest sites with Y-
    Coords")
diagnose.ppm(minor.fit, which = "x", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Minor group nest sites with X-
    Coords")
diagnose.ppm(minor.fit, which = "y", type = "pearson",
    cex.main=1.3,cex.lab=1.1,lwd=1, main="Minor group nest sites with Y-
    Coords")

# Covariate and cartesian coordinates (M2 models).
# Covariates
par(mfrow=c(2,3))
lurking(all.nests.combined, covariate=el, type="pearson", covname="Elevation
    (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="All nest sites and Elevation")
lurking(all.nests.combined, covariate=sl, type="pearson", covname="Slope
    degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="All nest sites and Slope")
lurking(rainy.combined, covariate=el, type="pearson", covname="Elevation
    (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Wet season nest sites and
    Elevation")
lurking(rainy.combined, covariate=sl, type="pearson", covname="Slope
    degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Wet season nest sites and
    Slope")
lurking(rainy.combined, covariate=wd, type="pearson", covname="Distance from water
    (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Wet season nest sites and Distance
    from water")
lurking(dry.combined, covariate=el, type="pearson", covname="Elevation
    (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Dry season nest sites and
    Elevation")
lurking(dry.combined, covariate=sl, type="pearson", covname="Slope
    degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Dry season nest sites and
    Slope")
lurking(major.combined, covariate=el, type="pearson", covname="Elevation
    (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Major group nest sites and
    Elevation")
```

```
lurking(major.combined, covariate=sl, type="pearson", covname="Slope
       degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Major group nest sites and
       Slope")
lurking(minor.combined, covariate=el, type="pearson", covname="Elevation
       (m)",cex.main=1.6,cex.lab=1.5,lwd=1, main="Minor group nest sites and
       Elevation")
lurking(minor.combined, covariate=sl, type="pearson", covname="Slope
       degree",cex.main=1.6,cex.lab=1.5,lwd=1, main="Minor group nest sites and
       Elevation")
# Against Cartesian coordinates
par(mfrow=c(2,5))
diagnose.ppm(all.nests.combined, which = "x", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="All nest sites with X-Coords")
diagnose.ppm(all.nests.combined, which = "y", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="All nest sites with Y-Coords")
diagnose.ppm(rainy.combined, which = "x", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Wet season with X-Coords")
diagnose.ppm(rainy.combined, which = "y", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Wet season with Y-Coords")
diagnose.ppm(dry.combined, which = "x", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Dry season nest sites with X-Coords")
diagnose.ppm(dry.combined, which = "y", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Dry season nest sites with Y-Coords")
diagnose.ppm(major.combined, which = "x", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Major group nest sites with X-Coords")
diagnose.ppm(major.combined, which = "y", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Major group nest sites with Y-Coords")
diagnose.ppm(minor.combined, which = "x", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Minor group nest sites with X-Coords")
diagnose.ppm(minor.combined, which = "y", type = "pearson",
       cex.main=1.3,cex.lab=1.1,lwd=1, main="Minor group nest sites with Y-Coords")

# Goodness-of-fit envelopes for fitted models.
# Covariates-only models (M1 models)
par(mfrow=c(2,2))
plot(envelope(all.nests.fit, fun=Kinhom, nsim=99, nrank=2, global=T,
control=list(expand=1)), xlim=c(200,1200),legend=F, main="All nest sites (K)",
       xlab="Distance (m)")
plot(envelope(rainy.fit, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), xlim=c(200,1200),legend=F, main="Wet season
       nests sites (K)", xlab="Distance (m)")
plot(envelope(dry.fit, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="Dry season nest sites (K)",
       xlab="Distance (m)")
plot(envelope(major.fit, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), xlim=c(100,1200),legend=F, main="Major group nest
       sites (K)", xlab="Distance (m)")
plot(envelope(minor.fit, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), xlim=c(100,800), legend=F, main="Minor group nest
       sites (K)", xlab="Distance (m)")

# Covariates + XY coords (M2 models)
par(mfrow=c(1,3))
plot(envelope(all.nests.combined, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), xlim=c(200,400),legend=F, main="All nest sites (K)",
       xlab="Distance (m)")
plot(envelope(rainy.combined, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), xlim=c(200,400),legend=F, main="Wet season nests
       sites (K)", xlab="Distance (m)")
plot(envelope(dry.combined, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), xlim=c(200,600),legend=F, main="Dry season nest
       sites (K)", xlab="Distance (m)")
plot(envelope(major.combined, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="Major group nest sites (K)",
       xlab="Distance (m)")
```

```
plot(envelope(minor.combined, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), xlim=c(0,400),legend=F, main="Minor group nest sites
       (K)", xlab="Distance (m)")

# M3 models (Combined models with Covariates, XY and higher-order interaction.
plot(envelope(AI.all, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="All nest sites", xlab="Distance
       (m)")
plot(envelope(AI.rainy, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="Wet season nest sites",
       xlab="Distance (m)")
plot(envelope(AI.dry, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="Dry season nest sites",
       xlab="Distance (m)")
plot(envelope(AI.major, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="Major group nest sites",
       xlab="Distance (m)")
plot(envelope(AI.minor, fun=Kinhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="Minor group nest sites",
       xlab="Distance (m)")

# extract AIC values of models
extractAIC(AI.all)

# Simulations from the fitted models
sim.all<-rmh(AI.all)
sim.rainy<-rmh(AI.rainy)
sim.dry<-rmh(AI.dry)
sim.major<-rmh(AI.major)
sim.minor<-rmh(AI.minor)

# Plot simulations from the fitted models.
par(mfrow=c(1,2))
plot(bg, col="darkolivegreen2", axes=T, main="All nest sites original and simulated
       points", xlab="X-Coordinates", ylab="Y-Coordinates", cex.lab=0.5,lwd=1)
plot(nests.unmarked, add=T, pch=12, cex=0.5, col="blue")
plot(sim.all, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Original points", "Points simulated from
       model"), pch=c(12,16), cex=c(1,1), pt.cex=c(1.2,1.2),
       col=c("blue", "red"), bty="n", text.width=4)

plot(bg, col="darkolivegreen2", axes=T, main="Wet season nest sites original and
       simulated points", xlab="X-Coordinates", ylab="Y-Coordinates",
       cex.lab=0.5,lwd=1)
plot(nests.rainy.unmarked, add=T, pch=12, cex=0.5, col="blue")
plot(sim.rainy, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Original points", "Points simulated from
       model"), pch=c(12,16), cex=c(1,1), pt.cex=c(1,1),
       col=c("blue", "red"), bty="n", text.width=4)

plot(bg, col="darkolivegreen2", axes=T, main="Dry season nest sites original and
       simulated points", xlab="X-Coordinates", ylab="Y-Coordinates",
       cex.lab=0.5,lwd=1)
plot(nests.dry.unmarked, add=T, pch=12, cex=0.5, col="blue")
plot(sim.dry, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Original points", "Points simulated from
       model"), pch=c(12,16), cex=c(1,1), pt.cex=c(1.2,1.2),
       col=c("blue", "red"), bty="n", text.width=4)

plot(bg, col="darkolivegreen2", axes=T, main="Major group season nest sites
       original and simulated points", xlab="X-Coordinates", ylab="Y-Coordinates",
       cex.lab=0.5,lwd=1)
plot(major, add=T, pch=12, cex=0.5, col="blue")
plot(sim.major, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Original points", "Points simulated from
       model"), pch=c(12,16), cex=c(1,1), pt.cex=c(1.2,1.2),
       col=c("blue", "red"), bty="n", text.width=4)
```

```
plot(bg, col="darkolivegreen2", axes=T, main="Minor group nest sites original and
       simulated points", xlab="X-Coordinates", ylab="Y-Coordinates",
       cex.lab=0.5,lwd=1)
plot(minor, add=T, pch=12, cex=0.5, col="blue")
plot(sim.minor, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Original points", "Points simulated from
       model"), pch=c(12,16), cex=c(1,1), pt.cex=c(1.2,1.2),
       col=c("blue", "red"), bty="n", text.width=4)

# Predict the fittes models
plot(predict.ppm(AI.all, type="trend")) # this plots fitted trend. could also plot
fitted conditional intensity (type="cif")
plot(predict.ppm(AI.rainy, type="trend"))
plot(predict.ppm(AI.dry, type="trend"))
plot(predict.ppm(AI.major, type="trend"))
plot(predict.ppm(AI.minor, type="trend"))
# end of point pattern analysis
####################################################


# Multitype point pattern analysis.
# Notes
# To model trend component for multitype points, we follow these:
# 1. Stationary point process: Each mark type has a different, constant intensity.
# 2. Non-stationary: Each mark has a separate, non-constant intensity. Therefore
# the intensity is modeled as a log-quadratic function of cartesian coordinates and
# covariates, multiplied by a constant factor depending on the mark. Therefore the
# coefficient obtained in the model
# for the mark type is the constant value that is used to determine the intensity
# function of the dataset.

# Basic plots to display marked patterns
# All nests
bg<-as.im(kgs.w)
plot(bg, col="darkolivegreen2", axes=F, main="All marked points", xlab="X-
       Coordinates", ylab="Y-Coordinates", cex.lab=0.5,lwd=1)
plot(major, add=T, pch=16, cex=0.7, col="blue")
plot(minor, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Major group nest sites", "Minor group nest
       sites"), pch=c(16,16), cex=c(1,1), pt.cex=c(1.2,1.2),
       col=c("blue", "red"), bty="n", text.width=4)
# Wet season
plot(bg, col="darkolivegreen2", axes=F, main="Wet season marked points", xlab="X-
       Coordinates", ylab="Y-Coordinates", cex.lab=0.5,lwd=1)
plot(major.rainy, add=T, pch=16, cex=0.7, col="blue")
plot(minor.rainy, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Major group nest sites", "Minor group nest
       sites"), pch=c(16,16), cex=c(1,1), pt.cex=c(1.2,1.2),
       col=c("blue", "red"), bty="n", text.width=4)
# Dry season
plot(bg, col="darkolivegreen2", axes=F, main="Dry season marked points", xlab="X-
       Coordinates", ylab="Y-Coordinates", cex.lab=0.5,lwd=1)
plot(major.dry, add=T, pch=16, cex=0.7, col="blue")
plot(minor.dry, add=T, pch=16, cex=0.7, col="red")
       legend("bottomleft", legend=c("Major group nest sites", "Minor group nest
       sites"), pch=c(16,16), cex=c(1,1), pt.cex=c(1.2,1.2),
       col=c("blue", "red"), bty="n", text.width=4)

# Summarize data
summary(nests)
summary(nests.rainy)
summary(nests.dry)
```

```
# Homogeneous Poisson models (Test for Complete Spatial Randomness and Independence
# (CSRI)) to test if the trend depends only on marks and not on spatial location or
# covariate

# Stationary multi-type poisson models
fit.null.all<-ppm(nests, ~marks)
fit.null.wet<-ppm(nests.rainy, ~marks)
fit.null.dry<-ppm(nests.dry, ~marks)

# Inhomogeneous (non-stationary) multi-type poisson models
all.marked<-ppm(nests, ~marks*polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl,
       2)+slp+hi+v, covariates=list(el=el, asp=asp, sl=sl, slp=slp, hi=hi, v=v))
rainy.marked<-ppm(nests.rainy, ~marks*polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl,
       2)+polynom(wd, 2)+v, covariates=list(el=el, asp=asp, sl=sl, wd=wd, v=v))
dry.marked<-ppm(nests.dry, ~marks*polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl,
       2)+v, covariates=list(el=el, asp=asp, sl=sl, v=v))

# Model diagnostics --goodness-of-fit envelopes
# NB Use multitype L and K functions which are Lcross.inhom and Kcross.inhom
plot(envelope(all.marked, Kcross.inhom, nsim=99, control=list(expand=1)), xlim=c(0,
       200), legend=F, main="All nest sites (Kcross Inhomogeneous)", xlab="Distance
       (m)")
plot(envelope(rainy.marked, Kcross.inhom, nsim=99, control=list(expand=1)),
       xlim=c(0, 100), legend=F, main="Wet season (Kcross Inhomogeneous)",
       xlab="Distance (m)")

# Models for Interaction between groups
# all
str.all<-matrix(c(100, 100, 100, 100), 2,2)#matrix of interaction radii
types<-levels(nests$marks)
int.all<-MultiStrauss(types, str.all)
fit.all.ms<-ppm(nests, ~marks*polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl,
       2)+slp+hi+v, covariates=list(el=el, asp=asp, sl=sl, slp=slp, hi=hi, v=v),
       int.all, rbord=0.05)

# wet season
str.rainy<-matrix(c(100, 100, 100, 100), 2,2)#matrix of interaction radii
types<-levels(nests$marks)
int.rainy<-MultiStrauss(types, str.rainy)
fit.rainy.ms<-ppm(nests.rainy, ~marks*polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl,
       2)+polynom(wd, 2)+v, covariates=list(el=el, asp=asp, sl=sl, wd=wd, v=v),
       int.rainy, rbord=0.05)

# dry season
str.dry<-matrix(c(330, 330, 330, 330), 2,2)
types<-levels(nests$marks)
int.dry<-MultiStrauss(types, str.dry)
fit.dry.ms<-ppm(nests.dry, ~marks*polynom(x,y,2)+polynom(el, 2)+asp+polynom(sl,
       2)+v, covariates=list(el=el, asp=asp, sl=sl, v=v), int.dry, rbord=0.05)

# Plot inhomogeneous multitype K functions
plot(envelope(fit.all.ms, Kcross.inhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="All nest sites (Kcross
       Inhomogeneous)", xlab="Distance (m)")
plot(envelope(fit.dry.ms, Kcross.inhom, nsim=99, global=T, nrank=2,
       control=list(expand=1)), legend=F,      main="Dry season (Kcross
       Inhomogeneous)", xlab="Distance (m)")
plot(envelope(fit.rainy.ms, fun=Kcross.inhom, nsim=99, nrank=2, global=T,
       control=list(expand=1)), legend=F, main="Wet season (Kcross Inhomogeneous)",
       xlab="Distance (m)")

# simulate the fitted models
sim.all<-rmh(fit.all.ms)
sim.rainy<-rmh(fit.dry.ms)
sim.dry<-rmh(rainy.marked)
```

```
# plot AICs
aic<-read.csv("aic_final.csv", h=T, sep=",", dec=".")
       max_y<-max(aic)
plot.colors<-c("blue", "forestgreen", "red", "black", "green")
plot(aic$All.nests, type="o", col=plot.colors[1], lwd=2, axes=F,
       ylim=c(3000,15000), ann=F)
axis(1, at=1:5, lab=c("Ho-Models","M1-Models","M2-Models","M3-Models","MT-Models"))
axis(2, las=1, at=3000*0:15000)
box()
lines(aic$Wet.season, type="o", pch=22, lty=2, lwd=2, col=plot.colors[2])
lines(aic$Dry.season, type="o", pch=23, lty=3, lwd=2,col=plot.colors[3])
lines(aic$Major.group, type="o", pch=24, lty=4, lwd=2,col=plot.colors[4])
lines(aic$Minor, type="o", pch=25, lty=5, lwd=2,col=plot.colors[5])
abline(v=4, col="purple", lty=3, lwd=2.5)
title(xlab= "Model category", col.lab="black")
title(ylab= "AIC Values", col.lab="black")
legend("bottom", legend=c("All nests", "Wet season", "Dry season", "Major group",
       "Minor group"), bty="n", cex=0.8, col=plot.colors, pch=21:25, lty=1:5)
       legend("topright", legend="M3 - Best model category", cex=1, bty="n",
       col="red")

# the end of analysis
#################################################################################
```

# Masters Program in Geospatial Technologies

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*Towards understanding the nesting behaviour of a critically endangered subspecies.*

**Funwi-Gabga Neba**

Dissertation submitted in partial fulfilment of the requirements
for the Degree of *Master of Science in Geospatial Technologies*

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