MODELLING MAMMAL SPECIES DIVERSITY AND ABUNDANCE IN SAVANNA ECOSYSTEMS USING GEOSTATISTICS AND CAMERA TRAP DATA

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Enschede, The Netherlands, March 2015

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ABSTRACT

Information on the spatial distribution and composition of biological communities is essential in designing effective strategies for biological conservation and management. The main objective of this study was to model the spatial distribution of mammal species diversity and abundance in Mpala savanna ecosystems from camera trap data using the geostatistical method. By incorporating with satellite-derived vegetation information, together with topography, water accessibility and human disturbance factors, the relationship between environmental factors and the mammal species diversity and abundance was reassessed with multiple regression analysis based on camera trap data. Then, the significant factors used to model the spatial distribution of the mammal species diversity and abundance using geostatistical method to evaluate the possibility of improving the mapping accuracy.

The study results indicated that the interspecific competition plays an important role that significantly effecting mammal species abundance. The abundance of herbivore species can explain 52% variability of carnivore species abundance. The abundance of mammal species has high correlation with species richness. In additionally, the human disturbance in this study area has no significant influence on the mammal species diversity and abundance. The topographic factors and water accessibility have negative influence on the mammal species diversity and abundance. The lager variation in vegetation growth in dry season results in low abundance and diversity of herbivore species, but the vegetation has no influence on abundance and diversity of carnivore species. Moreover, the woody coverage has no significant influence on the mammal species diversity and abundance. The study also shows that spatial distribution detected in my study indicates that there is a hotspot in the central part of Mpala with higher mammal species abundance in dry season.

This study shows that regression kriging can improve accuracy of estimates of mammal species abundance by considering the spatial dependence within wildlife populations and incorporating with environmental variables. The results of this study demonstrated that camera trap data with systemic sampling method can be used to assess mammal species diversity and abundance by geostatistical modelling method for wildlife conversation management.

This study suggests that spatial model developed in this work could be seen as a tool for wildlife management: firstly, continues spatial predictions give the effective and valuable information for the research sampling design. Secondly, it is better to plan conservation strategies looking at the hotspots of high abundance of mammal species.

Keywords: Camera traps, mammal species diversity and abundance, geostatistical modelling method, dry season, Mpala

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1. INTRODUCTION

1.1. Background

Assessments of future global changes predict that biodiversity will continue to decline (Pereira *et al.*, 2010). The loss of biodiversity poses one of the greatest threats to natural ecosystems which can lead to significant changes in community structure and ecosystem functioning throughout the world, especially African savanna that contains the earth's greatest diversity and density of large herbivore species (Sitters *et al.*, 2009a). Reducing the loss of biodiversity is key to ensuring the future well-being of our planet and humanity (Ahumada *et al.*, 2013).

Mammal species diversity and abundance has been under pressure in a long time in Africa. Between 1970 and 2005, wildlife abundance in African protected areas declined by 50% (Craigie *et al.*, 2010). Sixty-five percent of Kenya's wild animals live outside national parks and reserves (Western *et al.*, 2009). More than 50% of land that once supported wildlife is under agricultural production (Kinnaird & O'brien, 2012a). In Africa, many species' ranges are now restricted to protected areas (Kinnaird & O'brien, 2012a). Many management options promote conservation on private lands, including conservation easements and leases, compensation for depredation of livestock, payments for ecosystem services, hunting and game ranching (Kinnaird & O'brien, 2012a). There is widespread belief that wildlife conservation on private lands is integral to the persistence of large mammals (Kinnaird & O'brien, 2012a), and identification of spatial patterns in species diversity represents an essential task to be accounted for when establishing conservation strategies (Bacaro *et al.*, 2011).

Comprehensive information on the spatial distribution of species diversity and abundance and the relation with environmental factors represents an essential task for effective biodiversity conservation strategies or monitoring programs (Clément *et al.*, 2014). Geographical patterns of species diversity are one of the central topics in ecology and have gained much importance in recent years (e.g. Pino-del-Carpio *et al.*, 2014; Pettorelli *et al.*, 2010; Leyequien *et al.*, 2007). However, the distribution of mammal species in African landscapes especially in savanna ecosystems are spatially and temporally heterogeneous (Graham & Duda, 2011). Spatial scale has influence on the monitoring results and most research for monitoring species diversity has been collected on a large scale. That is attribute to heterogeneity of the unevenly distributed ecological conditions as well as local variations in response to specific niche requirements (Clément *et al.*, 2014).

Numerical modelling has been widely applied to estimate and analyze the spatial pattern of species distribution and to deal with all kinds of ecological, biogeographic and evolutionary problems. Due to the strongly varying in space and in time, a major challenge in spatially distributed model is that most ecological processes are heterogeneous (Mariethoz & Lefebvre, 2014). So far, there are many numerical models used to model the distribution of species. For example, the Species Distribution Models (SDMs) are a wide set of disciplines and designed to predict distributions of species from incomplete datasets and to identify environmental conditions associated with species distribution (Faleiro, Machado, & Loyola, 2013). Logistic models are used to estimate species distribution based on presence and absence data that is dichotomous. Most of the models are dealing with absence data that is more difficult to obtain. Moreover in most situations, field survey and photointerpretation are costly and inefficient. Models are informed by insufficient data, resulting in low accuracy of prediction. This problem has classically been addressed by geostatistical modelling technique. Geostatistical modelling technique, which has been developed mainly in the field of geography, is designed to model spatially dependent observations (Bacaro *et al.*, 2011). Previous studies have used different kinds of geostatistical technique to analyze the spatial distribution of ecological phenomena. For example, prediction of the distribution of vegetation based on the their spatial distribution and environmental variables (Miller *et al.*, 2007) with the development of remote sensing have produced efficient alternatives for predicting the spatial distribution through the geostatistical method.

Kriging, is a geostatistical tool for spatial prediction. It has proved extremely useful in various domains such as mining, soil science and ecology (Stein *et al.*, 1988; Kempen *et al.*, 2012). Kriging is a kind of variogram-based method. It defines spatial heterogeneity with a limited number of parameters such as variance, mean and variogram correlation range (Mariethoz & Lefebvre, 2014). In ecology, this technique has been applied to model African savanna woody tree density and canopy cover distribution (Adjorlolo & Mutanga, 2013); mapping patterns of the herbivore species abundance with populating data gaps (Kerrv *et al.*, 2013); combining different kriging method to improve the accuracy of the tropical tree richness mapping (Hernández-Stefanoni *et al.*, 2011) and identifying the spatial pattern of the regional bird species richness with the environmental factors (Bacaro *et al.*, 2011). Kriging prediction method has also become increasingly important in the ability to provide basis for predicting the mammal species diversity and abundance distribution by quantify their relationship with environmental factors. Current predictive species models (e.g. MaXent) are often developed without considering the spatial pattern that exists in bio-geographical data. However, ecosystem elements close to one another are more likely to be influenced by the same generating process and will therefore are similar (Miller *et al.*, 2007). Kriging can be used to predict the spatial pattern considering spatial auto-correlation, and some spatial pattern can be explained by the predictor variables (e.g. environmental factors) used in models.

To better understand the functioning of savanna ecosystems, insight into the determinants of species diversity distribution is necessary (Hagenah, Prins, & Olff, 2009). Especially in the dry season in savanna ecosystems, the increased attention to the high competition of natural resource between wildlife and livestock-related activities, has stimulated interest in understanding biophysical factors associated with indicators of species diversity and abundance. Compared to some previous wildlife conservation studies in Kenya, there is no surprise that integrating human disturbance factors into ecological model at human-wildlife coexisting system. Habitat destruction, human population growth as well as tourism have been noted to contribute significantly in increasing the pressure on wildlife. In Kenya, human disturbance factors are associated with bushmeat hunting, livestock-related activity and wildlife-based benefits (indirect benefits and direct benefits from a locally-owned tourism operation) (Georgiadis *et al.*, 2007; Sundaresan *et al.*, 2010). Gadd (2005b) thought the wildlife-based benefits were intended to offset costs and encourage tolerance of wildlife. In additionally, due to the seminomadic pastoral lifestyle in Kenya, pastoralism remains the economic mainstay and shares their pastoral lands with livestock and wildlife (Gutu *et al.*, 2010). For instance in Maasai Mara National Reserve which has the largest abundance of wildlife in Kenya, attributes its losses to increasing numbers of boundary settlements which is accompanied by illegal wildlife harvesting and livestock grazing (Ogutu *et al.*, 2011). The most private land benefits wildlife and people by expanding habitat and extending wildlife derived economic development (Gadd, 2005b). During the dry season due to limited water availability, pastoralists tend to move their cattle towards remaining water bodies (Sitters *et al.*, 2009a). Cattle concentration are may cause local changes in plant structure and composition around these water bodies, which affect the distribution of mammal species.

Not only the human disturbance factors, other environmental factors, like vegetation, terrain and water accessibility, will also have an impact on the loss of mammal species diversity and abundance (Pino-del-Carpio *et al.*, 2014). In recent years, many studies have tried to identify environmental factors affecting distribution of mammal species diversity and abundance. The biomass-biodiversity hypothesis predicts that in the presence of abundant and reliable resources, species biomass is high and become more specialized, allowing more species per unit area (Guo, 2007). In savanna ecosystems, low biomass ecosystems are expected to be associated with low diversity, while at intermediate biomass diversity is highest (Mutowo, 2010). Species richness often increases with increasing productivity and then decreases as productivity increases further (Aarrestad *et al.*, 2011). In additionally, water availability during dry seasons is an important factor structuring the distribution of mammal species abundance (Sitters *et al.*, 2009). In response, wildlife managers often set up permanent water supplies by creating artificial water points or augmenting existing seasonal sources (Shannon *et al.*, 2009). However, the terrain have influence on the distribution of water, therefore affecting the distribution of mammal species. The higher elevation with lower temperature that is suitable area for animal in dry season (Mugerwa *et al.*, 2012).

The category of mammal species based on their diet is necessary to take into consideration when identify factors affecting the distribution of mammal species diversity and abundance. As for the role of herbivore in structuring plant communities and determining community compositions is well recognized, herbaceous plant species evenness is an important determinant of the small mammal community (Wigley *et al.*, 2014). The local extirpation of large herbivores has consequences for entire ecosystems, because of their role in maintaining the diversity of predators and primary producers. Carnivores are also sensitive to changes in the environment (Pettorelli *et al.*, 2010).

1.2. Camera trapping, GIS and remote sensing

Camera trapping method has long been used to survey and monitor the occurrence of wildlife species around the world (Park *et al.*, 2011). Since the research of mammal species diversity needs repeated data and intensive survey, camera traps are a useful, efficient, cost-effective, and easily replicable method to monitor mammal species distribution (Ahumada *et al.*, 2013). Traditional ground survey to obtain the data of species diversity is time-consuming and labor-intensive. With the arrival of digital camera traps in the last decade, and their increased affordability, many projects have started using them as tools for assessing and inventorying terrestrial vertebrates. Camera traps have been used in the previous studies to either discover new species or analyze the species diversity (Liu *et al.*, 2013; Cove *et al.*, 2013). In additionally, data from camera trap offers the opportunity to model the ecological state variable of interest (e.g., abundance or probability of occurrence of species) while taking into account the detection process (e.g., the probability of detecting a species given that it occurs at the site) (Ahumada *et al.*, 2013). This allows for unbiased indicator estimation, making camera trap surveys extremely useful for monitoring programs aimed at measuring progress towards biodiversity conservation management.

Camera trap sampling avoids bias inherent in aerial and ground sampling as well as providing representative estimates of species richness, abundance, and distribution, mostly the nocturnal mammals (Kinnaird & O'brien, 2012a). In comparison with other field sampling methods (e.g. line transect census and field survey), camera trapping method is the most suitable method for mammal inventory allowing a rapid assessment of wildlife conservation status, standardization and reducing the error of identification of the photographs as well as human influence (Silveira, Jácomo, & Diniz-Filho, 2003). As for the cost of camera for surveying large area, the camera trapping method can be handled more easily with relatively low costs in a long term run (Mugerwa *et al.*, 2012; Marcus Rowcliffe *et al.*, 2011). Initially, camera-trapping was relatively untargeted and data collection was not standardized. Over time, these efforts have been replaced by more systematic sampling approaches, often concentrated on identifying individual animals in a mark-recapture framework *(Park et al.*, 2011), or using path-occupancy approaches to assess detection probabilities for species presence/absence (O'Brien *et al.*, 2010; Ahumada *et al.*, 2013; Cove *et al.* 2013). Due to many nocturnal animals in savanna, it is hard for traditional census survey to do an inventory of such species but, since camera traps use infrared motion sensors, they can be replicated seasonally or annually under the same field sampling conditions while active 24 hours per day. Other advantages also includes the accuracy of species determination as well as density (Abi-Said & Amr, 2012; Bernard *et al.*, 2013; Ahumada *et al.*, 2011).

Remote sensing for long has been proposed as a relatively cheap and repaid method to surrogate environmental factors (Hernández-Stefanoni *et al.*, 2011). The development of GIS and remote sensing products such as hyper-temporal vegetation indices i.e. Moderate-resolution Imaging Spectroradiometer (MODIS), Landsat data and Digital Elevation Model (DEM) have provided scientists and wildlife managers opportunities to link camera trap data to the products for wildlife conservation management. Numerous remotely detectable parameters that can be extracted from remote sensing products, such as Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI) and woody coverage, can thus be used as ancillary variables. For example, Biomass and plant productivity of ecosystems vary in time and space, and the spatial heterogeneity in productivity is hypothesized to affect local abundance of individuals and species distribution (Leyequien *et al.*, 2007). The most commonly used surrogate for quantifying above-ground biomass of ecosystems and productivity is NDVI. It is an indicator of the greenness of vegetation canopies and able to separate vegetation from other materials and therefore correlated to faunal species occurrence and diversity (Oindo, 2002). DEM derived slope and aspect can also be used to characterize savanna ecosystems. In additionally, the spectral heterogeneity must be related to the complexity and structure of the landscape, properties which are related to habitat heterogeneity and therefore species diversity. For most research of species diversity, data got from plot scale. Using remote sensing can be extrapolated to cover a larger region of interest and estimate habitat suitability.

1.3. Problem statement

Geostatistical method is an effective and convenient method, which enhances the accuracy of estimations of spatial distribution of species diversity by considering different covariance - of environmental factors (Webster & Oliver, 2007; Hernández-Stefanoni *et al.*, 2011). It is clear that describing spatial patterns of species using complete censuses of various taxa is challenging, because of the costs associated to the collection of species distribution data. Camera traps are a useful, efficient, cost-effective, and easily replicable method to monitor mammal species distribution. Due to the systematic sampling approach of camera traps, it is possible to use geostatistical method to model the spatial distribution of mammal species diversity and abundance (Bacaro *et al.*, 2011). However, there is less research using geostatistical method to analyze spatial distribution of the mammal species diversity and abundance based on camera trap data.

The Mpala provides an example of an area where wildlife conservation is being conducted successfully on private lands. It is a living laboratory to test the ways that humans and wildlife can coexist. The importance of the Mpala range is that little of it is formally protected and predominantly unfenced, yet wildlife abundance is second in Kenya only to the renowned Masai Mara National Reserve (Georgiadis *et al.*, 2007). Wildlife share the largely unfenced landscape with varying densities of livestock. In addition to it, Mpala has constructed many artificial water pond and human activities in this area has been controlled and managed in a proper way. In this regard, Mpala is an idea area to study the spatial distribution of mammal species diversity and abundance and its response to the biological and anthropogenic factors.

Although the relationship between mammal species and environmental factors is well documented but previous studies have mostly considered natural environmental factors or livestock factors separately, to explain the distribution of mammal species. The distribution of mammal species diversity and abundance during dry season has been greatly fragmented by multiple threats, such as water distribution, livestock-related activities, increasing human populations and tourism. Due to the seminomadic pastoral lifestyle, there is a conflict between human community and wildlife conservation. Successful conservation of mammal species diversity on private land requires finding of the relationship between distribution of mammal species diversity and environmental factors. This is necessary for conservation and is expected to support efficient biodiversity conservation management.

1.4. Research Objectives

1.4.1. General objective

The aim of this study is to model the spatial distribution of the mammal species diversity and abundance during the dry season in Mpala from camera trap data using geostatistics.

1.4.2. Specific objectives

- To estimate the mammal species diversity and abundance during the dry season in Mpala from camera trap data
- To determine factors affecting the mammal species diversity during dry season in Mpala using multiple regression
- To determine factors affecting the mammal species abundance during dry season in Mpala using multiple regression
- To model the spatial distribution of mammal species diversity and abundance based on their food habit (i.e. carnivore, herbivore and omnivore) during the dry season in Mpala using regression kriging geostatistical method

1.4.3. Research questions

- What are the mammal species diversity and abundance during the dry season in Mpala?
- What factors significantly drive the mammal species diversity (i.e. carnivore, herbivore and omnivore) during the dry season in Mpala? What are the most critical factors?
- What factors significantly drive the mammal species abundance (i.e. carnivore, herbivore and omnivore) during the dry season in Mpala? What are the most critical factors?
- What are the distribution patterns of the mammal species diversity and abundance during the dry season in Mpala?

2. MATERIALS AND METHOD

2.1. Study area

The Mpala Ranch (referred to as "Mpala") is a private wildlife area and cattle ranch administered by a consortium of academic and wildlife institution (Gadd, 2005b). Study area –Mpala (Figure 1, longitude: 36°45'; latitude: 00°10') lies beneath the shadow of Mt. Kenya, in the center of Laikipia County, Kenya. It covers an semi-arid savanna region of 200 $km^2$and lies at an elevation between 1561-1826m above sea level (MRC, 2014).

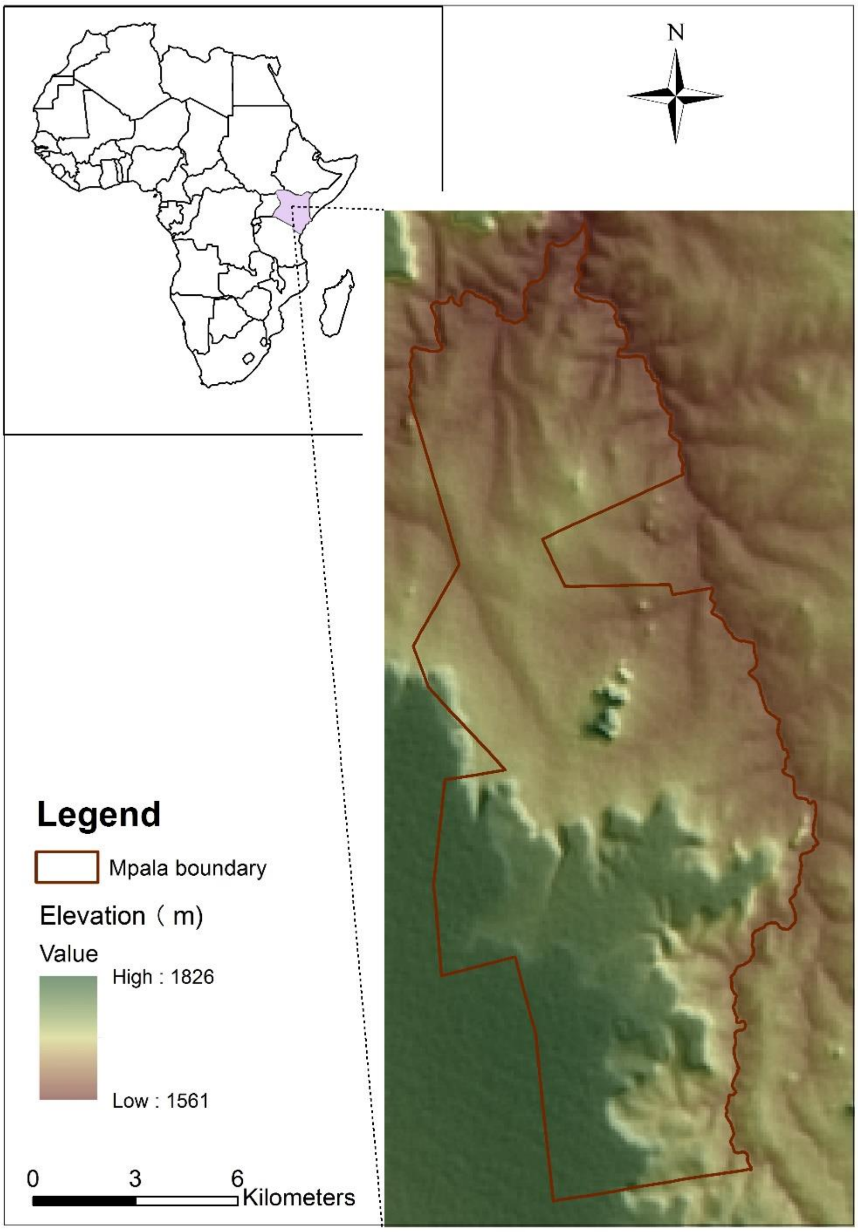

Figure 1. The location of study area

The climate is semi-arid, with an average annual rainfall of about 550 mm. There are short rains from October to December, and longer rains from April to June (Shorrocks, Cristescu, & Magane, 2008). Rainfall peaks in April-May, August and October and a consistent dry season in the months of January to March (Almer *et al.*, 2013). The average maximum temperature is 28°C and the minimum 14°C. Soils are 'black cotton' vertisols characterized by very high clay content and poor drainage (MRC, 2014).

Mpala is made up of savanna and dry woodland and bordered by two rivers the Ewaso Ngiro and the Ewaso Narok (MRC, 2014). Apart from the permanent rivers, Mpala has twenty-two water dams majorly for the domesticated ranch cattle but also shared among the array of wildlife found here. The vegetation is primarily grassland, with tree and shrub patches spread over the landscape. The woodland cover is dominated by acacia. While grasses are perennial grasses with discontinuous layers of herbs and shrubs. The northern of Mpala is underlain by dissected Archean terrain with thin dark red sandy loams (latosols). The south western of Mpala is characterized by open woody land.

Wildlife here include elands (*Tragelaphus oryx Pallas*), Grant's gazelles (*Gazella granti Brooke*), steinbucks (*Raphicerus campestris Thunberg*), elephants (*Loxodonta Africana Blumenbach*) and giraffes (*Giraffa camelopardalis L.*) (Okello *et al.*, 2008). Resident predators include lions (*Panthera leo Linnaeus*), leopards (*Panthera pardus Linnaeus*), cheetahs (*Acinonyx jubatus Schreber*), wild dogs (*Lycaon pictus Temminck*) (Gadd, 2005b).

Mpala for long has been known as a working cattle private ranch. Only 2.1% of the area is set aside exclusively for wildlife in (private) fenced reserves (Georgiadis *et al.*, 2007). Elsewhere, wildlife is free to move in and out of Mpala. Mpala facilitates and exemplifies sustainable human-wildlife co-existence and the advancement of human livelihoods and quality of life. Mpala hosts an active research center- the Mpala Research Center and security camps are strategically located in the ranch. Some of the project carried here including the camera trap project. There are long term electric fenced research plots constructed for research purposes with active research activities being conducted in them (MRC, 2014). Mpala practices cattle ranching using the traditional Maasai livestock herding method where they use thorns to protect the cattle at night from the predators. In Mapla, land owners who tolerate wildlife engage in tourism businesses and augment their income by leasing property for British army-training exercise (Kinnaird & O'brien, 2012a).

2.2. Camera traps

There were a total of 97 camera stations distributed all around the unfenced landscape of Mpala. Each station had one camera. All cameras were packed in camouflaged boxes and attached to the base of trees close to the ground. Camera locations were marked using a portable GPS for easy relocation during checking or collection. The coordinates of these cameras are based on geographic coordinate system (UTM37N) and use meter-"m"- as their unit. Camera traps were operational 24 hours per day. They use infrared motion sensors to capture any movement. When the animals walk through the camera, the snap photos of themselves taken included, 3 images were taken consecutively. The sampling did not involve collection of animal species in the field but only the photographs. At the end of each deployment, memory cards were recovered, and images were identified and processed by the staff of Mpala Research Center into Excel datasheet.

The sampling method was based on the standardized systematic grid with cell size of 2km × 2 km. Camera were put all across Mpala, away from main trails and with no bait. Due to altitude variation, some camera were not placed on the exact position. The allowed spatial error was 50m from the main camera station. The survey randomly chose stations for setting cameras, because of time and staff constraints (Jenks *et al.*, 2011). The camera traps were set in the field in two sets. Half the stations were place during the first three weeks of dry season and the last bunch was set during the after three weeks from the first bunch setting.

Each camera was sampled 19-23days based on the expected life of batteries and when the roads were passable to set the cameras (Kinnaird & O'brien, 2012b).

The camera survey was conducted at 96 locations in Mpala between 2010 and 2012 during the dry season (January and February, Figure 2), resulting in 106,964 records. Camera traps at an additional location did not yield data. The possible reasons for this: 1) the staff forgot to set up the camera or unlock the SD card when set in the station; 2) the camera was destroyed by animals when they passed by.

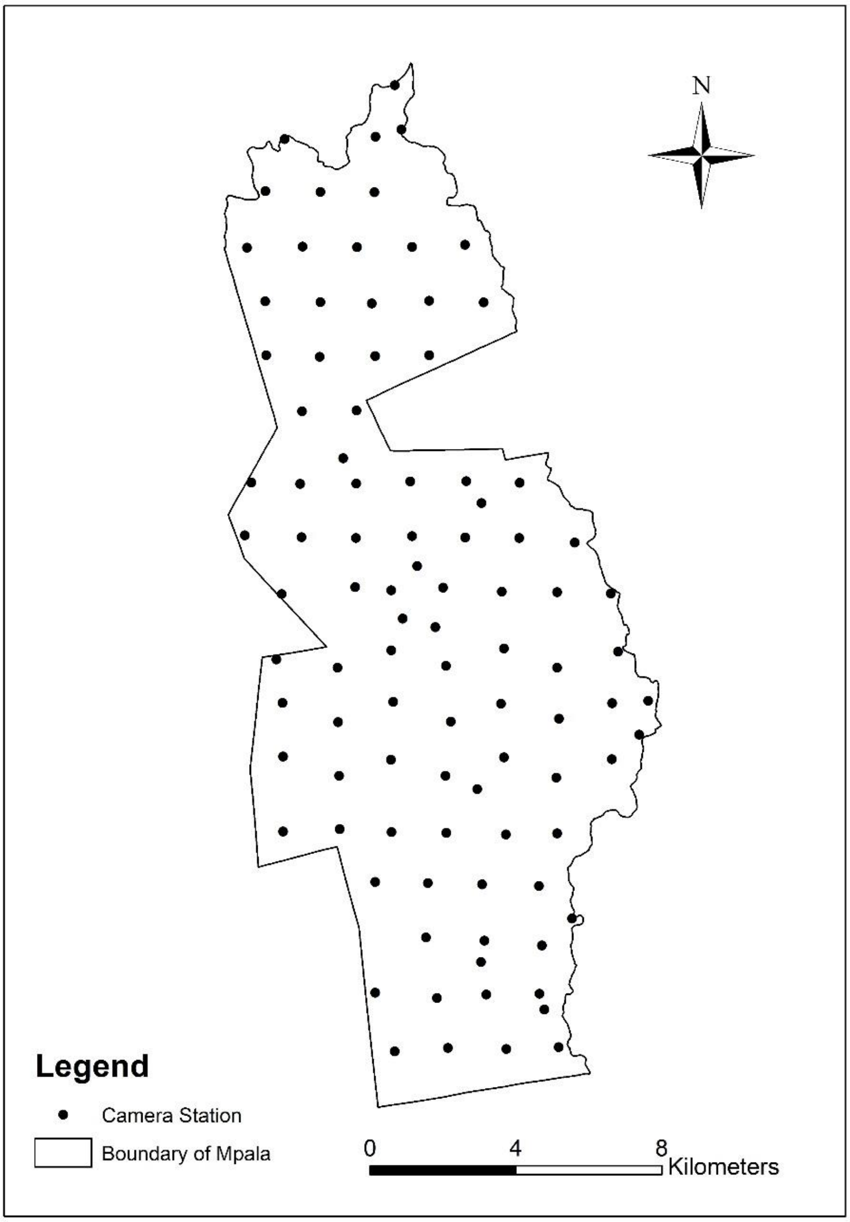

Figure 2. Locations of the camera trap station in Mpala

2.3. Data preparation

2.3.1. Camera trap data processing

The total number of detected wildlife species is 57. The cameras stamp each picture with the time and date, so we know when every animal was photographed (Figure 3). Classification of mammal data followed the mammal taxonomy of the IUCN Red List and J.Kingdon (1997), I identified the class, family, body size, population and trend of each mammal species. The full list of 42 mammal species identified from this data can be found in the supporting information (Table S1 in Appendix).

After the classification of species, I deleted the blank images, such as misfires, and duplicated records (79, 535 records). Because of the setting up and checking of the cameras in the field, there are some recorded images named "set up", "check", "pick up". "Misfire" means there is no data in the images. The number of valid camera trap photographs recorded mammal species is 7, 621 records. Then, I grouped photographic sequences into independent photographic events following O'Brien *et al.* (2003). If the time between consecutive photographs of the same species was more than 0.5 hours apart, it is assumed as an independent photographic event. (O'Brien et al. 2003; Park et al., 2011). Photos with more than one individual in the frame were counted as one detection for the species (: Jenks, K. E., Chanteap, P., Damrongchainarong, K., Cutter, P., Cutter, P., Redford, T., Lynam & Howard, J., and Leimgruber, 2011). Furthermore, there are camera trap records named human, vehicle, cow, goat, sheep, camel and donkey (1,076 photographic events after deleting duplicated data). These photographic events used for estimating the probability of human disturbance occurrence, which is the number of photo captures per 100 trap nights at each camera station.

Figure 3. Camera trap photo from Mpala Research Center

2.3.2. Field data collection

According to the research requirements, two types of data were collected in the field. One is the ground truth data of training and testing samples for woody coverage classification. The other one is the data of human disturbance. Field work was carried out from September 10 to September 25, 2014. For human disturbance, I focused on the area that has more human activity and included all the human settlement. The locations of cattle bomas, the ranch house, the Mpala village, the Clifford house, pump houses, security bases, research plots and research Centre were collected in the fieldwork.

The woody coverage was defined according to Food and Agriculture Organization of the United Nations (FAO). FAO defines woody vegetation as those plants that uses wood as part of their structural support including herbaceous plants with developed woody stems. The selection of sample site based on stratified random sampling is suggested to avoid bias. The sample plots were pre-determined before fieldwork based on Google earth image interpretation of the tree canopy covers. Percentage cover estimate ranges used for each class were determined based on interpretation of the Google earth images and expert knowledge on spatial woody cover of the study area (Table 1). The sampling routes were designed along the roads that are all around Mpala. Some sample plots located on either side of the road with a distance of 500m at least, and kept a distance of 2-3 km from each other in case of spatial autocorrelation. The woody coverage of plots was measured based on visual estimations. Finally, 115 samples of woody coverage were collected. Figure 4 shows the spatial distribution of the sample plots.

The instruments used during the fieldwork included IPAQ 200 series, topographic maps, measuring tape 50m, a compass and a digital camera. IPAQ 200 series, which includes handheld Global Position System (GPS), was used to collect plot location coordinates with a spatial error of 3 meters. The size of the sample plots was 50m×50m. This plot size was assumed as large enough to represent the information of the Landsat 8 image – 30m×30m pixel size.

Table 1. The category of woody coverage

Class	Percentage of woody coverage	Ground data collected
High woody cover	>=50%	48
Medium woody cover	15-50%	48
Low woody cover	<=15%	19

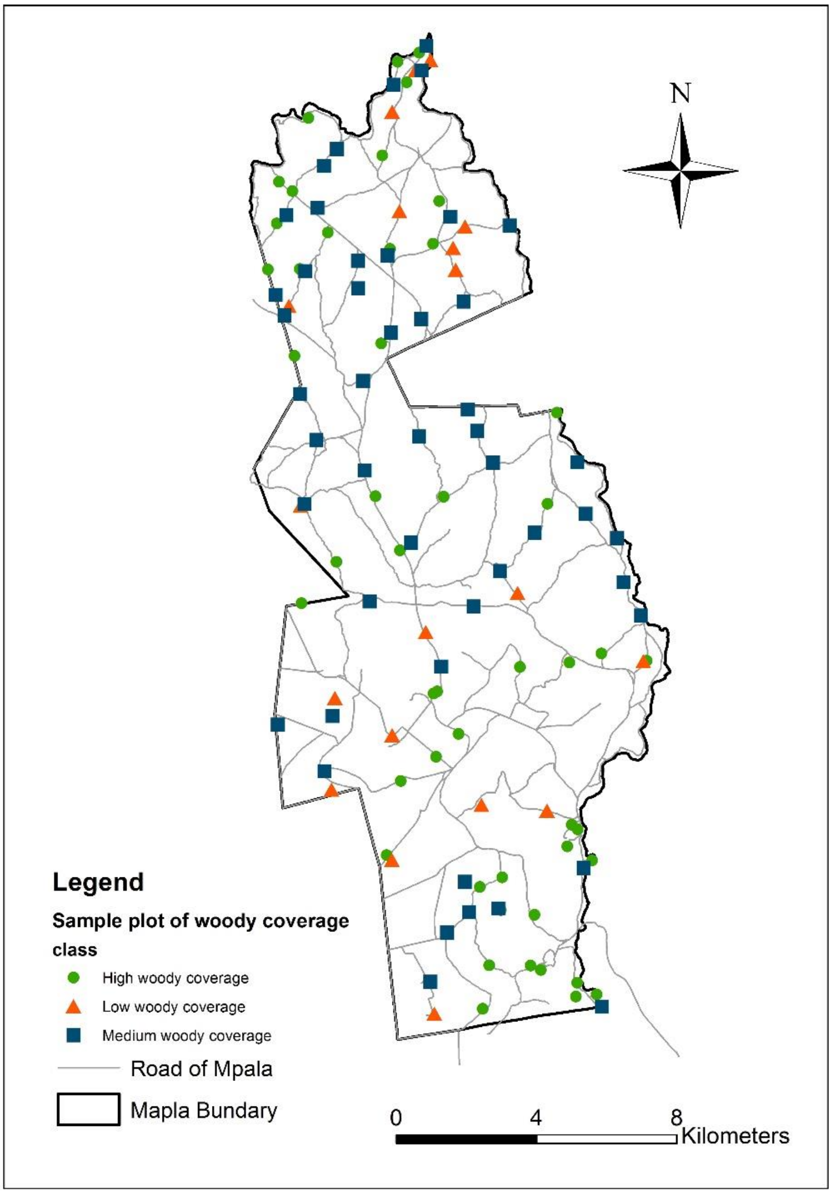

Figure 4. The spatial distribution of the woody coverage sample plots in Mpala

2.3.3. Woody cover mapping from Landsat 8 satellite image

Landsat 8 satellite image was used for woody coverage classification. The Landsat 8 satellite image data for Oct. 1, 2014, was downloaded from the United States Geological Survey (USGS) website (http://landsat.usgs.gov/landsat8.php). Landsat 8 image has 12 bands totally. Two spectral bands include coastal aerosol and cirrus bands. One band is panchromatic with spatial resolution of 15m. The other bands are with the spatial resolution of 30m. Clouds were nearly absent in the acquired Landsat data, and no smog appeared in the atmosphere. Therefore, it was assumed that air condition effect on the atmospheric correction of Landsat data could be ignored.

The method used to classify woody cover was supervised classification using Erdas Imagine 2014. The maximum likelihood classifier (MLC) is used in supervised classification methods. MLC proceeds by selecting the largest posterior probability rather than minimum distance (Atkinson & Lewis, 2000). It assumes that the training samples are normally distributed in spectrum feature space, and calculates the probability that a given pixel belongs to a specific class. Woody coverage in this study was classified into three categories: high woody cover, medium woody cover and low woody cover. Reference data for training (60%) and testing (40%) was collected during the fieldwork. Figure 5 displays the woody coverage classification result. From the visual interpretation, there are large areas of medium woody coverage. In the south of Mpala, there are more areas of high woody coverage than those in the north.

Furthermore, the Cohen's kappa was used to assess the image classification accuracy. The Cohen's kappa statistic is a chance-corrected measure of agreement. Landis et al. (1977) suggested that model performance could be judged as almost excellent (kappa>0.81), fair to substantial (0.81 > kappa>0.21), or poor (kappa < 0.2). Both overall accuracy and kappa statistics were produced to evaluate the classified image. The classification result obtained an overall accuracy of 86.96% and a kappa coefficient of 0.79. According to the judge rule of the Cohen's kappa, this classification of woody coverage was good. The result of classification was converted to percentage cover of the study area, then used in modelling the relationship of environmental factors with mammal species diversity and abundance.

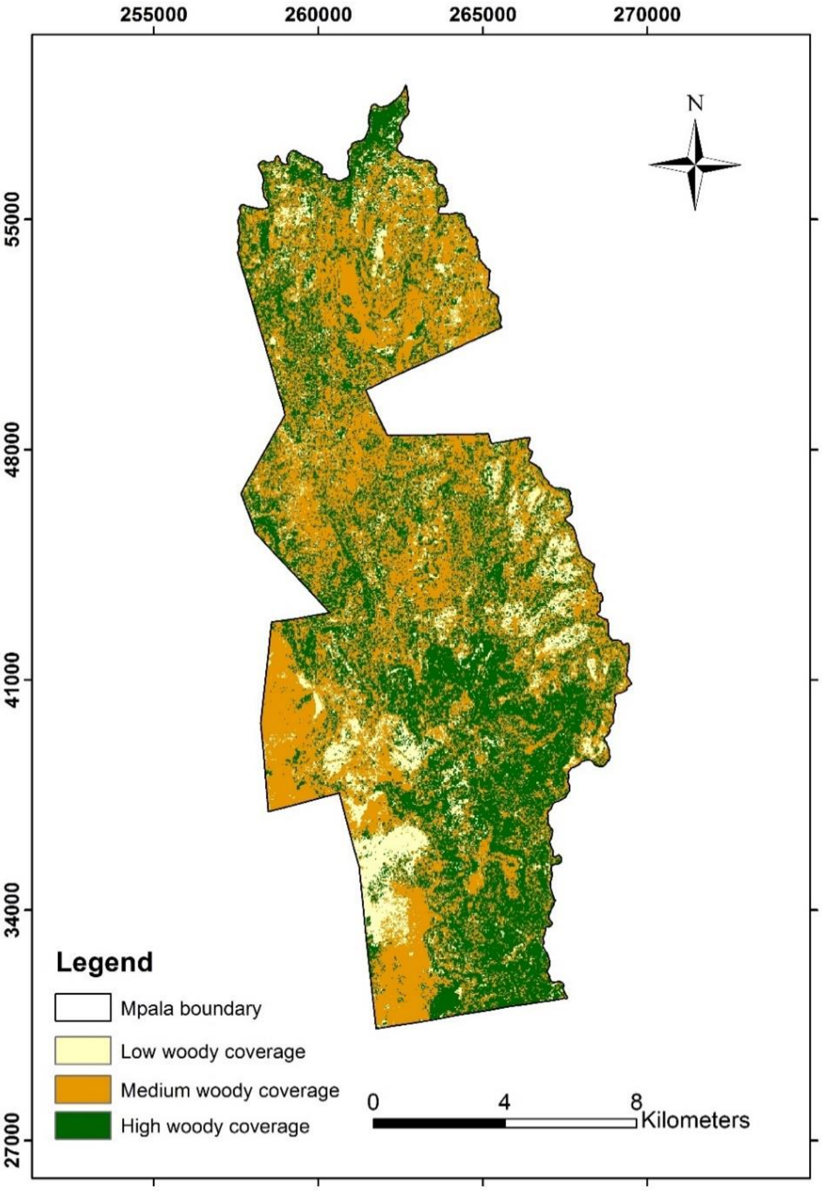

Figure 5. The woody coverage of the Mpala

2.3.4. MODIS data pre-processing

NDVI (Normalized Difference Vegetation Index) is derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) to calculate both seasonally specific and longer-term measures of vegetation biomass. MODIS data is available for 2010 to 2012. It is 12-month (January to December) time series of 16-day composites (Global MOD13QI product from the Terra satellite, 250m resolution, downloaded from http://lpdaac.usgs.gov). MODIS has high temporal resolution products of vegetation indexes, so that it is not only able to reduce the problem of cloud but also provide information on the spatial and temporal dynamics of land surface.

MODIS NDVI data with a relatively coarse spatial resolution reveals phonological characteristics of biomass. Compared to some previous wildlife assessment studies in Kenya, the properties of the NDVI time-series can be summarized in a variety of related indices (Nathalie Pettorelli *et al.*, 2005). The inter annual variation of the maximum NDVI can be used to assess whether vegetation coverage over a number of years is actually stable in an area, or highly variable. High standard deviations correspond to areas with large variations in vegetation composition and growth. Mean NDVI is the average primary productivity of vegetation (Oindo & Skidmore, 2002).

In order to reduce the potential noise of cloudiness but also keep high fidelity of the data, MODIS NDVI data was cleaned and smoothed using an adaptive Savitzky-Golay filter in the TIMESAT program using ENVI (Jönsson & Eklundh, 2004). After smoothing 12-month multi-temporal NDVI data, it was combined to one image with 23 bands. The NDVI data was mosaicked and re-projected from sunsiudol to the UTM37N, including mean, standard deviation, maximum, minimum NDVI per year and mean NDVI during the dry season. All the indices of NDVI were used as environmental variables for multiple regression analysis.

2.3.5. Description of dataset

All the GIS second-hand data came from the GIS office in Mpala. Table 2 lists the second-hand data and their derived data.

Table 2. Description of other second-hand data and their derived data

Data	Derived data
Slope	90m Digital Elevation Model (DEM)
Aspect	90m Digital Elevation Model (DEM)
Elevation	90m Digital Elevation Model (DEM)
Distance to river	Vector data of rivers in Mpala
Distance to water pond	Location of water pond
Boundary of Mpala	Vector data
Distance to road	Vector data of roads in Mpala

Abiotic factors included vegetation, topography and water accessibility. In this study, there are two indicators used to surrogate water accessibility: one is the distance to river; the other one is the distance to water pond. Based on the distribution of rivers in Mpala, distance to river that is distance to the nearest river from each sampling site (i.e. camera station), can be computed using the distance tool in Spatial Analysis ArcGIS. Distance to water pond is the Euclidean distance from each camera station to the nearest water pond with ArcGIS using the locations of water pond. Elevation, slope and aspect are used as topographic factors. These factors can be computed using the surface tool, while elevation information can be directly extracted from DEM using the extraction tool in ArcGIS.

In addition to abiotic factors, there are some social environmental factors, such as the probability of human disturbance occurrence, the distance to roads and the distance to bomas, which can be classified as human disturbance factors. In Mpala, there is boma for herding, as well as the village and school for staff. Pastoralists use donkeys and camels for transportation. The locations of boma are usually changed every 10 or 20 years depending on the soil condition. Moreover, staff and researchers in Mpala Research Center use vehicles as transportation and to set, check and pick up the cameras in the field. The locations of cattle bomas, the ranch house, the Mpala village, the Clifford house, the pump house, the security base, research plots and the research center were used to calculate the Euclidean distance to the nearest camera station by ArcGIS as a layer named "distance to human disturbance". The probability of human disturbance occurrence was calculated from camera trap data. All the data was resampled to the spatial cell size of 250m and clipped to the subset of the study area. The environmental factors used in this study are shown in Figure 6.

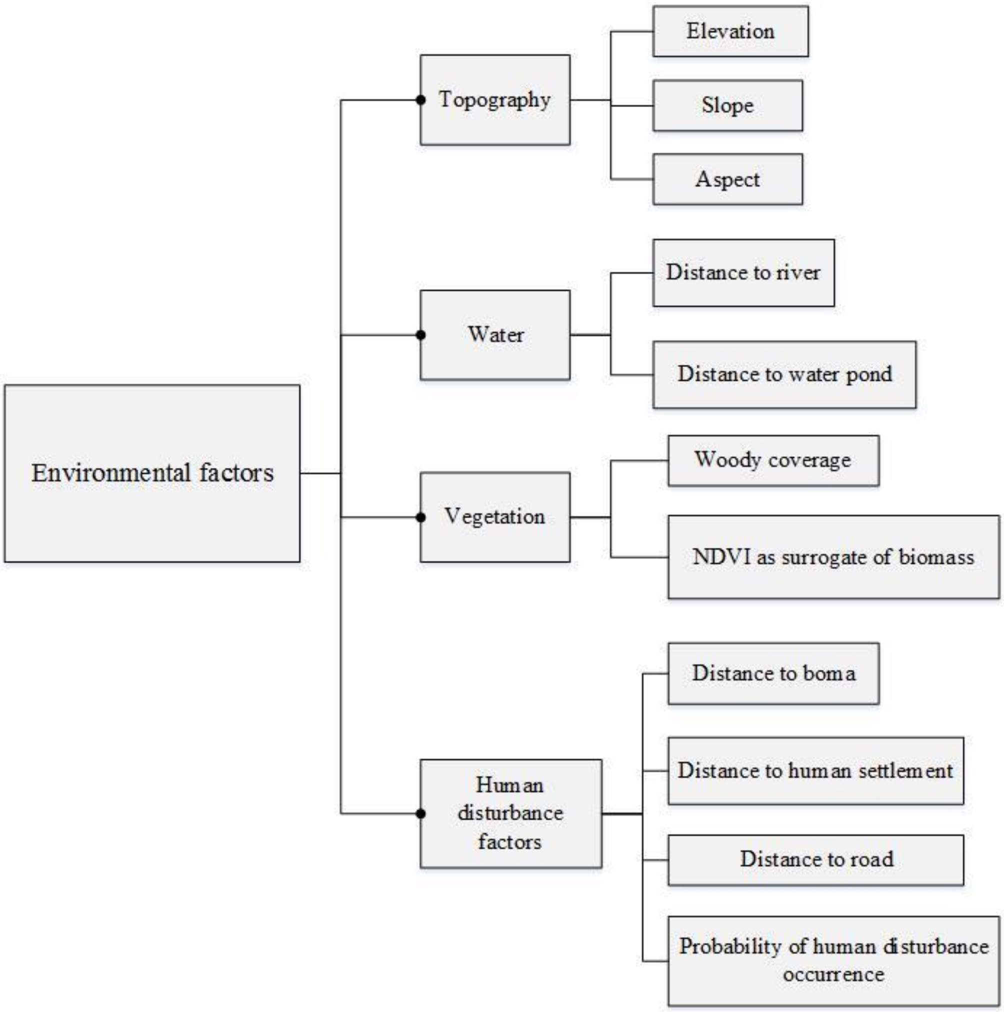

Figure 6. Characterizing the structure of environmental factors

2.4. Selection and calculation of species diversity index and abundance index

The species diversity index and abundance index as a surrogate of wildlife play a crucial role in biodiversity conservation and management. There are three most popular diversity index including species richness, the Shannon-Wiener diversity index and the Simpson index.

The species richness (SR) is the most general and popular index in biodiversity research. The species richness is an intuitive measure of species diversity, which can also be defined as the total count of species in a sample unit or other specified area. In this study, I calculated the species richness using the amount of photographic events of species in each camera station generally.

The Shannon-Wiener diversity index and The Simpson index differ from SR in that, in addition to depicting the number of species in each community, they also take into account the relative abundance of each species (Yessoufou *et al.*, 2013). Shannon index used as index that is more influenced by the relative proportion of the most numerous species in the sample (Konečný, Koubek, & Bryja, 2009). It assumes that the species that only appear once should not have the same weight as the species that appear several times in the sample when modelling the species diversity distribution. The Simpson index measures the degree of concentration when individuals are classified into types. Both of these two indices consider the importance of species abundance. However, in this study, there is only relative abundance measured from camera trap data. The accuracy of relative abundance will have influence on the calculation of the Shannon-Wiener index and the Simpson index. So I don’t use the Shannon-Wiener diversity index and the Simpson index to estimate the mammal species diversity from camera trap data.

The relative abundance index is used as indicator of mammal species abundance. In most monitoring programs, it is prohibitively expensive to estimate the actual abundance of species in a defined area. Many researches use occupancy as a surrogate for single specie abundance estimation, not for total wildlife abundance (Mackenzie & Nichols, 2004; Stanley & Royle, 2005; Cove *et al.*, 2013; Mackenzie *et al.*, 2014). Some researches use the relative abundance index (RAI) that is standard for camera trap surveys to estimate the wildlife abundance (Jenks *et al.*, 2011). Because I examine the total mammal community from camera traps in this study, I use a relative abundance index rather than unbiased estimates of absolute abundance for mammal species. RAI assumes that all detections for each specie is the same for all camera traps over all days, which reflects the number of photographic events per time unit-100 trap days (Ahumada et al., 2013; Kinnaird & O’brien, 2012a; Park *et al.*, 2011). In this study I followed Kinnaird & O’brien (2012a) and assumed that the RAI was a useful index for all mammal species in Mpala. So I used the number of photographic events of mammal species per time unit- 100 trap days as RAI at each camera station.

2.5. Modelling the spatial distribution of mammal species diversity and abundance

The detailed continual information of spatial distribution of mammal species is usually lacking (Bacaro *et al.*, 2011; Clément *et al.*, 2014). Field investigation is not precise and may be subjectively influenced by sampling routes or records so that the distribution records may not represent actual species distribution. Due to the cost and operational time of batteries, camera traps cannot be set in every corner around the study area and for a long continual time. Geostatistical modelling method offers the possibility to generate scenarios of what unknown reality could be (Mariethoz & Lefebvre, 2014).

2.5.1. Geostatistical model

The kriging is developed using traditional statistical methods and are based on the implicit assumption that the distribution of vegetation is random and, therefore, each observation is independent (Miller *et al.*, 2007). Variogram was used (Venables & Smith, 2014) to build the experimental variogram for each index. The fitting models were Spherical, Linear, Exponential and Gaussian. The range, nugget and sill of each variogram was used for index interpretation of the spatial dependence. All statistical computing used the gstat, rgdal and raster library of the R software (Venables & Smith, 2014).

2.5.1.1. Ordinary Kriging

Ordinary Kriging (OK) is a technique used in geostatistics to estimate property values for locations where the property has not been measured. In this study, the property was measured by mammal species diversity index and abundance index. The mammal species diversity index and abundance index as a primary variable provides information on the structure of the spatial variability which helps define the size and shape of the neighborhood for interpolation (Hernández-Stefanoni *et al.*, 2011). For this tool to be used it is required that the spatial dependence defined by the semi-variogram exists. The semi-variogram is computed from (Bickel et al., 2007):

$$\mathrm{y(h)} = \frac{1}{2n}\sum\left(Z(x_i) - Z(x_i + h)\right)^2$$

Where $\mathrm{Z}(x_i)$ is the primary variable (mammal species diversity or abundance index), sampled in camera station i; $\mathrm{Z}(x_i + h)$ is the value of variables sampled in other camera station separated from x_i, by a discrete distance h determined from the $\mathrm{Z}(x_i)$ and $\mathrm{Z}(x_i + h)$ coordinates; n represents the number of pairs of observations separated by h, and $\mathrm{y(h)}$ is the estimated semi-variance value for all pairs at the lag distance h. $\mathrm{y(h)}$ increases with the h distance until a maximum value at which it stabilizes, at a level corresponding to the limit distance of spatial dependence, which is the range. Measurements located at greater distances than the range have random distribution and are therefore independent among themselves; beyond this distance, classic statistics can be applied (Grego, Vieira, & Lourenção, 2006).

The kriging interpretation was computed over 250m×250m grid cells that were created based on the coordinates of the camera stations. I normalized the data using the most common method (i.e. logarithmic or square root transformations); then, an exponential variogram was chosen to fit the sample variogram using different cutoffs and bin widths to find the best fitting model. The sample points were interpolated using Ordinary Kriging (OK) in order to visualize the prediction and variance values.

2.5.1.2. Regression kriging

Regression kriging (RK) differs in the way it utilizes the ancillary information to estimate the target variable at un-sampled locations (Hernández-Stefanoni *et al.*, 2011). RK combines a simple or a multiple regression model with ordinary kriging of regression residuals to estimate the primary variable, i.e. this method addresses both the spatial dependence of observations and the relationship between the dependent variable (mammal species diversity or abundance index) and the ancillary variables (environmental factors) (Webster & Oliver, 2007). The RK estimator of mammal species diversity or abundance $Z_{rk}(x)$ obtained as a linear function between mammal species diversity and abundance and both environmental factors and the kriged estimate of spatially correlated residual values$\varepsilon_{ok}(x)$, using the following equation:

$$Z_{rk}(x) = Z_r(x) + \varepsilon_{ok}(x)$$

To obtain regression kriging estimates, simple linear regression model or multiple linear regression model was used to predict different index. Based on multiple regression analyses, I added environmental factors as explanatory variables to improve the accuracy of the prediction.

Many ecological models that attempt to predict the environmental suitability for species as a function of a set of selected environmental variables have been developed so far. In this study, using regression kriging, it is possible for me to get continuous data of species distribution patterns. The regression kriging interpretation was computed over 250m×250m grid cells.

2.5.1.3. Model evaluation

It is possible to fit several models and find their goodness-of –fit; however the goodness-of-fit depends on the cut off and number of bins. The sum of squares errors (SSErr) used as criteria to estimate theoretical models' goodness-of-fit. The lower the better (Venables & Smith, 2014).

The performance of interpolation method with different environmental factors was assessed by leave-one-out cross-validation (City, 1988), that is mean error (ME) and root mean square error (RMSE). When ME is close to 0, there is less bias produced by model. But for RMSE, the lower RMSE indicates that the accuracy of the prediction is better. The difference map was used to visualize the difference between ordinary kriging and regression kriging models. The operation was executed in R software.

2.6. Multiple regression analysis

Multiple regression analysis is used when one is interested in predicting a continuous dependent variable from a set of independent variables. Some literatures about species diversity use multiple regression as method to examine the relationship with environmental factors. Badgley & Fox (2000) used linear multiple regression to determine which of the climatic and physiographical variables have a statistically significant, unique contribution to the prediction of mammal species density in North America. Real *et al.* (2003) preformed multiple regressions of each terrestrial mammal species group's species richness on the environmental, human and spatial variables, to determine the amounts of variation explained by these factors in each Argentinian province. Qian & Ricklefs (2012) applied multiple regression analysis to distinguish the effects of geographic distance and environmental dissimilarity on global patterns of species turnover in different classes of terrestrial vertebrates on a global scale. Stepwise multiple regressions were used to identify the strongest predictors of biotic specialization in Africa and, separately, in both continental hemispheres (Fernández & Vrba, 2005). Therefore, multiple regression analysis is chosen as the modelling method for determining factors affecting the distribution of mammal species diversity and abundance.

The fitting of the multiple regression model was accomplished by a stepwise procedure. Firstly, I created spatially explicit indices representing each of environmental factors and extracted values for each sampling location (i.e. camera station) (Burton *et al.*, 2012). A general explorative analysis of pairwise variable correlation will be carried out. Correlations were calculated between variables (Table S2 in Appendix). I examined and evaluated covariance for all environmental variables and species diversity. After this, these explanatory variables for modelling the variation in the distribution of mammal species diversity will be used in multiple regression analysis. In order to detect multicollinearity in the set of variables, variance inflation factor (VIF) was used to exclude the multicollinearity factors. The best predictor subset will be obtained finally and regression coefficients estimated with significant coefficients at 5% level.

Stepwise model selection uses the Akaike information criterion (AIC). The AIC is a measure of the relative quality of a statistical model for a given set of data. That is, given a collection of models for the data, AIC estimates the quality of each model relative to the other models. Hence, AIC provides a means for model selection based on different combination of environmental factors as explanatory variables. The lower AIC, the model is better.

Multiple regression methods attempt to predict the mammal species diversity and abundance as a function of a set of selected environmental variables. Significant regression coefficient of determination in multiple regression analysis can be examined by F-test. If the F-test of a regression coefficient is significant, it indicates that the variable in question influences dependent variable significantly while controlling for other independent explanatory variables. The different models are compared based on the coefficient of determination obtained (R^2) from a multiple regression that was used to measure the attribution of independent variables in structural variance. I used the models that R^2 is higher than 50% to do regression kriging.

3. RESULTS

3.1. Mammal species diversity and abundance in the dry season in Mpala

After processing of all camera trap data, there are 4,062 independent photographic events, of which 73.5% (2,986 events) are of mammal species, 26.5% (1,076 events) are humans, vehicles, donkeys, camels and cattle. Species captured on photo included 42 mammal species (Table S1 in Appendix). Based on their food habits, the mammal species are classified into three groups, i.e. carnivore, herbivore and omnivore and the number of the species in each group is shown in Table 3. Due to the small amount of omnivore species (5.7%), this study only focusses on the analysis of the carnivore and herbivore in Mpala.

Table 3. Classification of mammal species based on their food habit

Category	Number of species
Carnivore	17
Herbivore	20
Omnivore	5

The total number of photographic events of the carnivore species is 270. The number of photographic events of each carnivore species is shown in Figure 7 The number of photographic events per carnivore species ranges from 1 to 109 events. Of these species, 8 species were documented in more than 10 events, and 9 species had number of photographic events around 5. Spotted hyena has the largest number of photographic events (109 events, 40.4%).

The total number of photographic events of the herbivore species is 2, 546 events; Figure 8 shows the number of photographic events of each species. The number of photographic events per herbivore species ranges from 2 to 986 events. 9 species were documented in less than 20 events. Guenther's dik-dik has the largest number of photographic events (986 events, 38.7%).

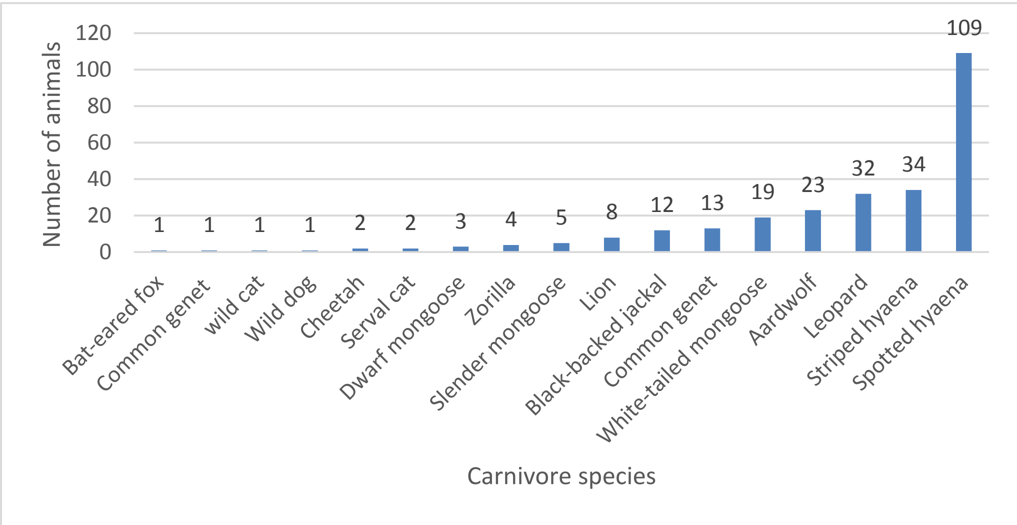

Figure 7. Number of photographic events of each carnivore species captured in the dry season in Mpala

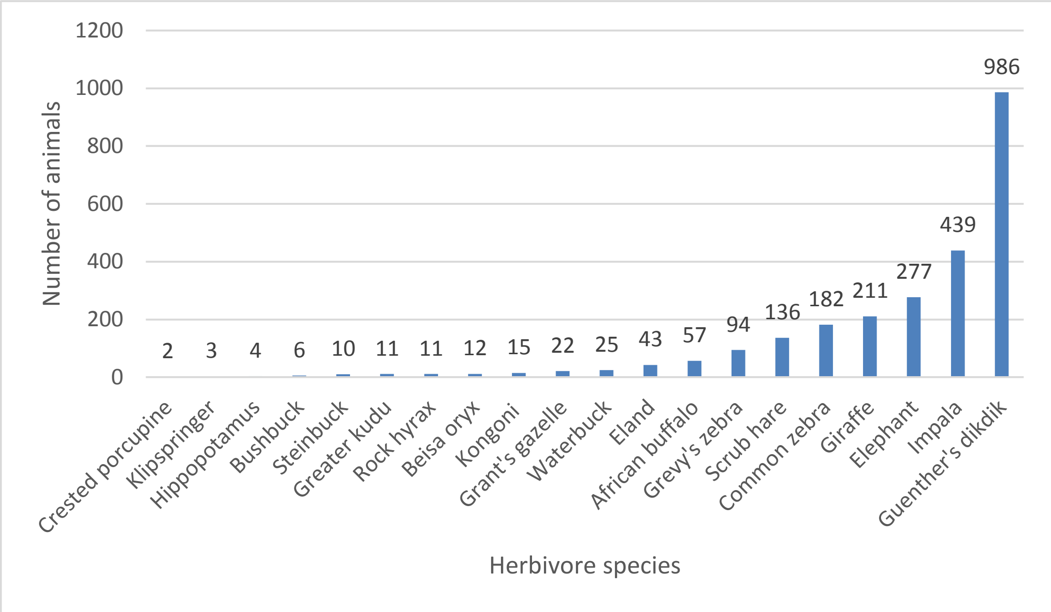

Figure 8 Number of photographic events of each herbivore species captured in the dry season in Mpala

3.1.1. Spatial distribution of mammal species richness

The mammal species richness of each camera station was calculated based on the number of photographic events for each camera station. The spatial distribution of the total mammal species richness of each station is shown in Figure 9. Figure 10 and 11 show the species richness of carnivore species and herbivore species at each station. The range of mammal species richness is between 1 and 17 at each station. The range of carnivore species richness is between 0 and 6 at each station. The range of herbivore species richness is between 1 and 9 at each station.

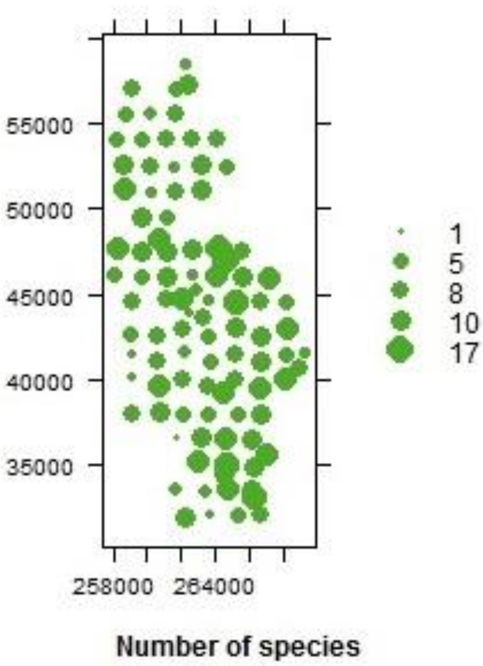

Figure 9. Distribution of the total mammal species richness

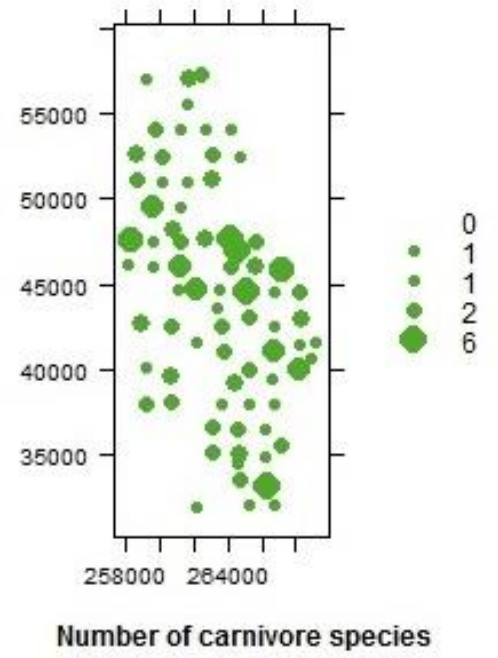

Figure 10. Distribution of carnivore species richness

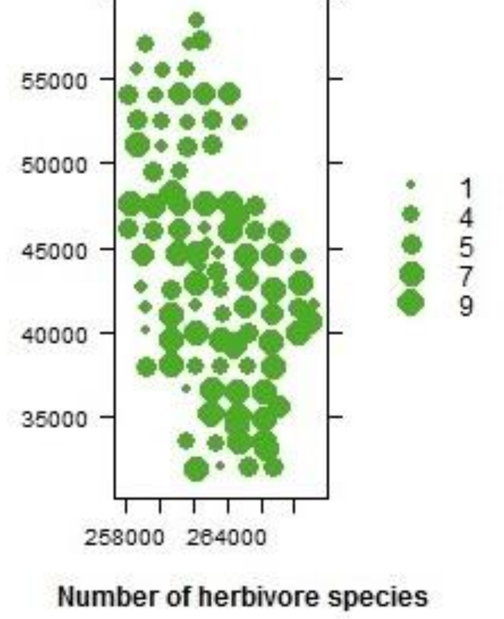

Figure 11. Distribution of herbivore species richness

3.1.2. Spatial distribution of relative abundance index of the mammal species

As for the character of camera trap data, the RAI of the mammal species is used to estimate the abundance of mammal species in the dry season in Mpala. The RAI of the total mammal species is shown in Figure 12. It ranges from 0.01 to 0.84 at each station. The distribution of the RAI of the carnivore species is shown in Figure13 with a range from 0.01 to 0.08 at each station. The figure 14 shows the spatial distribution of the RAI of the herbivore species. It ranges from 0.04 to 0.66 at each station.

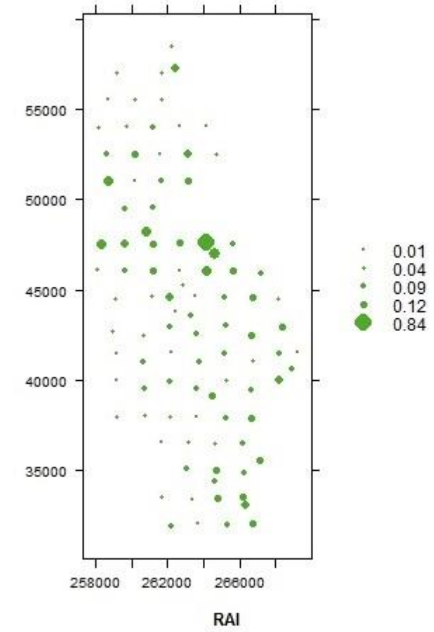

Figure 12. Distribution of the mammal species abundance

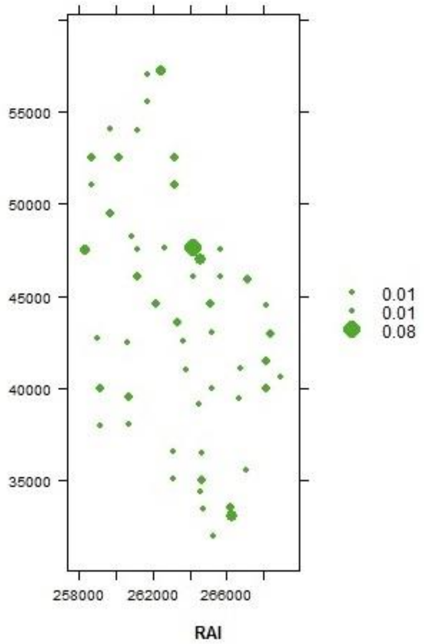

Figure 13. Distribution of the carnivore species abundance

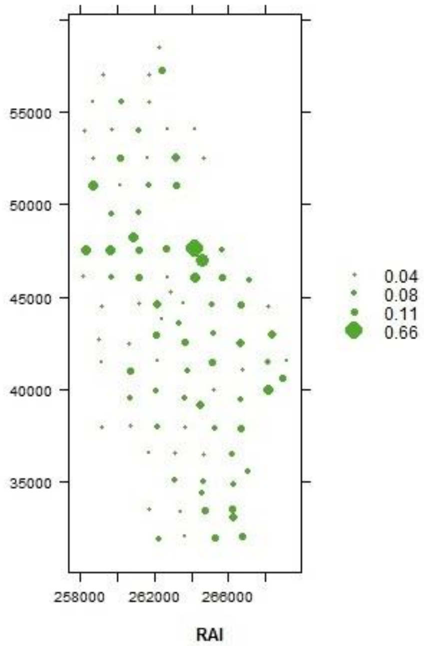

Figure 14. Distribution of the herbivore species abundance

3.2. Factors affecting the diversity of mammal species in the dry season in Mpala

I used the multiple linear regression analysis to estimate which factor significant affects the species richness. Due to multicollinearity in the set of environmental variables, mean and minimum of NDVI in the dry season and maximum NDVI were excluded (VIF > 10) from explanatory variables. The best explanatory variables subset was obtained and regression coefficients estimated.

3.2.1. Factors affecting the species richness of the total mammal species diversity in the dry season in Mpala

Model selection for the multiple linear regressions between the explanatory variables and species richness (Table 4) shows that only one model successfully and significantly explained the mammal species richness (Table 5). The best model for predicting the dependent variable includes RAI of the mammal species, mean NDVI, minimum NDVI, standard deviation of NDVI in the dry season, elevation, aspect and distance to water pond (AIC=-138.55, p<0.0001). Of these explanatory variables, the RAI of the mammal species, mean NDVI and standard deviation of NDVI are significant with a p value < 0.001 (Table 5). The mammal species richness in the dry season in Mpala is negatively correlated with minimum NDVI, standard deviation of NDVI in the dry season, elevation, aspect and, distance to water pond, are positively correlated with the RAI of the mammal species and the mean NDVI.

Table 4. Candidate models considered in the analyses of the relationship between environmental factors and mammal species richness in the dry season in Mpala

Model identification	Model description
1	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5\left(stedd_{NDVI_{dry}}\right) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road}) + B_{15}(\mathrm{RAI}_{mammal})$
2	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5\left(stedd_{NDVI_{dry}}\right) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road})$
3	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5\left(stedd_{NDVI_{dry}}\right) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage)$
4	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5\left(stedd_{NDVI_{dry}}\right) + B_6(distance_{human\ settlement}) + B_7(woody\ coverage)$
5	$y = B_0 + B_1(pro_{human}) + B_2(distance_{human\ settlement}) + B_3(distance_{boma}) + B_4(distance_{water\ pond}) + B_5(distance_{road})$
6	$y = B_0 + B_1(mean_{NDVI}) + B_2(stedd_{NDVI}) + B_3(min_{NDVI}) + B_4\left(stedd_{NDVI_{dry}}\right) + B_5(distance_{river}) + B_6(distance_{water\ pond}) + B_7(woody\ coverage) + B_8(Aspect) + B_9(Slope) + B_{10}(Elevation)$
7	$y = B_0 + B_1(mean_{NDVI}) + B_2(stedd_{NDVI}) + B_3(min_{NDVI}) + B_4\left(stedd_{NDVI_{dry}}\right) + B_5(distance_{river}) + B_6(distance_{water\ pond}) + B_7(woody\ coverage)$
8	$y = B_0 + B_1(mean_{NDVI}) + B_2(stedd_{NDVI}) + B_3(min_{NDVI}) + B_4\left(stedd_{NDVI_{dry}}\right) + B_5(distance_{river}) + B_6(distance_{water\ pond})$
9	$y = B_0 + +B_1(distance_{river}) + B_2(distance_{water\ pond})$
10	$y = B_0 + B_1(mean_{NDVI}) + B_2(stedd_{NDVI}) + B_3(min_{NDVI}) + B_4(distance_{water\ pond}) + B_5(woody\ coverage)$
11	$y = B_0 + B_1(woody\ coverage) + B_2(Aspect) + B_3(Slope) + B_4(Elevation)$
12	$y = B_0 + B_1(pro_{human}) + B_2(distance_{human\ settlement})$

y is mammal species richness as dependent variable, RAI_{mammal} is RAI of mammal species, pro_{human} is probability of human disturbance occurrence, $distance_{water\ pond}$ is distance to water pond, $distance_{human\ settlement}$ is distance to human settlement, $distance_{road}$ is distance to road and $distance_{boma}$ is distance to boma.

Table 5. The best prediction model for the mammal species richness in the dry season in Mpala

Predictor variable	Parameters estimate	P-value	Adjusted R^2
Intercept	6.44	<0.001	
RAI of mammal species*	0.84	<0.001	0.47
Mean NDVI*	0.03	0.026	
Minimum NDVI	-0.03	0.095	
Standard deviation of NDVI in dry season*	-0.08	<0.001	
Elevation*	-2.32×10^{-3}	0.03	
Aspect	-7.01×10^{-4}	0.12	
Distance to water pond	-7.17×10^{-5}	0.16	

*variable included in the model with p<0.05

3.2.2. Factors affecting the species richness of the carnivore species in the dry season in Mpala

Considering the influence between different classes of mammal species, candidate models for the multiple regression analyses shows in Table 6 and only one model was successfully and significantly explained the species richness of the carnivore species after model selection (AIC=-98.32, $p<0.0001$). The RAI of herbivore species was a significant coefficient with a p value < 0.01(Table 7). The species richness of carnivore species was negatively correlated with the distance to river and the mean NDVI, but positively correlated with the species richness of herbivore species and the RAI of the herbivore species.

Table 6. Candidate models considered in the analysis of the relationship between environmental factors and the species richness of carnivore species in the dry season in Mpala

Model identification	Model description
1	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5\left(stedd_{NDVI_{dry}}\right) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road}) + B_{15}(sr_{omni}) + B_{16}(RAI_{herbi}) + B_{17}(RAI_{omni}) + B_{18}(sr_{herbi})$
2	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5\left(stedd_{NDVI_{dry}}\right) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road}) + +B_{15}(RAI_{omni}) + B_{16}(RAI_{herbi})$
3	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5\left(stedd_{NDVI_{dry}}\right) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road})$
4	$y = B_0 + B_1(sr_{omni}) + B_2(RAI_{herbi}) + B_3(RAI_{omni}) + B_4(sr_{herbi})$
5	$y = B_0 + B_1(sr_{herbi}) + B_2(sr_{omni})$
6	$y = B_0 + B_1(RAI_{herbi}) + B_2(RAI_{omni})$

y is dependent variable, sr_{herbi} is the species richness of herbivore species, sr_{omni} is the species richness of omnivore species, RAI_{herbi} is the RAI of herbivore species, RAI_{omni} is the RAI of omnivore species, pro_{human} is probability of human disturbance occurrence, $distance_{water\ pond}$ is distance to water pond, $distance_{human\ settlement}$ is distance to human settlement, $distance_{road}$ is distance to road and $distance_{boma}$ is distance to boma.

Table 7. The best prediction model for the species richness of the carnivore species in the dry season in Mpala

Predictor variable	Parameters estimate	P-value	Adjusted R^2
Intercept	1.84	0.10	
Species richness of herbivore species*	0.36	0.011	0.28
RAI of herbivore species*	0.54	0.003	
Mean NDVI	-0.01	0.13	
Distance to river	-2.04×10^{-3}	0.16	

*variable included in the model with p<0.05

3.2.3. Factors affecting the species richness of the herbivore species in the dry season in Mpala

Model selection for the multiple regression analyses between the species richness of the herbivore species and the explanatory variables shows in Table 8 and only one model was successfully and significantly explained the species richness of the herbivore species (AIC=111.11, $p<0.0001$, Table 9). The species richness of the herbivore species is negatively correlated with the maximum NDVI in the dry season, the aspect and the distance to water pond, but positively correlated with the RAI of the total mammal species, the species richness of the carnivore species and the mean NDVI. The RAI of the total mammal species is significant coefficients with a p value < 0.001.

Table 8. Candidate models considered in the analysis of the relationship between environmental factors and the species richness of the herbivore species in the dry season in Mpala

Model identification	Model description
1	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5(max_{NDVI\_dry}) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road}) + B_{15}(RAI_{mammal}) + B_{16}(sr_{carni}) + B_{17}(sr_{omni})$
2	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5(max_{NDVI\_dry}) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road}) + B_{15}(RAI_{carni}) + B_{16}(RAI_{omni})$
3	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5(max_{NDVI\_dry}) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road})$
4	$y = B_0 + B_1(RAI_{carni}) + B_2(RAI_{omni}) + B_3(sr_{carni}) + B_4(sr_{omni})$
5	$y = B_0 + B_1(sr_{carni}) + B_2(sr_{omni})$
6	$y = B_0 + B_1(RAI_{carni}) + B_2(RAI_{omni})$

y is dependent variable, sr_{herbi} is the species richness of herbivore species, sr_{omni} is the species richness of omnivore species, RAI_{herbi} is the probability of herbivore species occurrence, RAI_{omni} is the probability of omnivore species occurrence, RAI_{mammal} is probability of mammal species occurrence, pro_{human} is probability of human disturbance occurrence, $distance_{water\ pond}$ is distance to water pond, $distance_{human\ settlement}$ is distance to human settlement, $distance_{road}$ is distance to road and $distance_{boma}$ is distance to boma.

Table 9. The best prediction model for the species richness of the herbivore species in the dry season in Mpala

Predictor variable	Parameters estimate	P-value	Adjusted R^2
Intercept	4.79	0.18	
RAI of mammal species*	1.79	<0.001	0.35
Species richness of carnivore species	0.29	0.05	
Mean NDVI*	0.062	0.028	
Maximum NDVI in dry season*	-0.049	0.005	
Aspect	-0.0028	0.087	
Distance to water pond*	-0.00038	0.034	

*variable included in the model with p<0.05

3.2.4. Factors affecting the relative abundance of the total mammal species in the dry season in Mpala

Using candidate models in Table 10 for model selection, the multiple linear regressions between the explanatory variables and the RAI of the total mammal species as dependent variable showed that one model was successfully and significantly explained the RAI of the total mammal species (AIC=-201.67, p<0.0001, Table 11). The species richness of the total mammal species is significant coefficient with a p value < 0.001. The RAI of the total mammal species is positively correlated with the species richness of the total mammal species and the distance to river, but negatively correlated with the elevation.

Table 10. Candidate models considered in the analysis of the relationship between environmental factors and the RAI of the total mammal species in the dry season in Mpala

Model identification	Model description
1	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5(max_{NDVI\_dry}) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage) + B_{11}(Aspect) + B_{12}(Slope) + B_{13}(Elevation) + B_{14}(distance_{road}) + B_{15}(sr)$
2	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5(max_{NDVI\_dry}) + B_6(distance_{human\ settlement}) + B_7(distance_{boma}) + B_8(distance_{water\ pond}) + B_9(distance_{river}) + B_{10}(woody\ coverage)$
3	$y = B_0 + B_1(pro_{human}) + B_2(mean_{NDVI}) + B_3(stedd_{NDVI}) + B_4(min_{NDVI}) + B_5(max_{NDVI\_dry}) + B_6(distance_{human\ settlement})$

y is dependent variable, pro_{human} is probability of human disturbance occurrence, $distance_{water\ pond}$ is distance to water pond, $distance_{human\ settlement}$ is distance to human settlement, $distance_{road}$ is distance to road and $distance_{boma}$ is distance to boma.

Table 11. The best prediction model for the RAI of the total mammal species in the dry season in Mpala

Predictor variable	Parameters estimate	P-value	Adjusted R^2
Intercept	1.87	<0.001	
Species richness of mammal species*	0.98	<0.001	0.50
Elevation	-1.31×10^{-3}	0.12	
Distance to river*	1.42×10^{-4}	0.039	

*variable included in the model with p<0.05

3.2.5. Factors affecting the relative abundance of the carnivore species in the dry season in Mpala

Model selection based on candidate models in Table 6, the multiple linear regressions between the explanatory variables and the RAI of the carnivore species as dependent variable shows that two model were successfully and significantly explained the RAI of the carnivore species (Table 12). After model selection, the best model for predicting the dependent variable includes the RAI of the herbivore species, the RAI of the omnivore species, the probability of human disturbance occurrence, the woody coverage and the distance to river (AIC=-639.97, p<0.0001). Of these explanatory variables, the RAI of the herbivore species is significant coefficients with a p value < 0.001. The RAI of the carnivore species is positively correlated with the RAI of the herbivore species, the RAI of the omnivore species and the probability of human disturbance occurrence, but negatively related to woody coverage and distance to river.

Table 12. The best prediction model for the RAI of the carnivore species in the dry season in Mpala

Predictor variable	Parameters estimate	P-value	Adjusted R^2
Intercept	0.006	0.036	
RAI of omnivore species*	0.2	<0.001	0.57
RAI of herbivore species*	0.008	0.026	
Probability of human disturbance occurrence	9.94×10^{-3}	0.15	
Woody coverage	0.02	0.087	
Distance to river*	-1.99×10^{-5}	0.025	

*variable included in the model with p<0.05

3.2.6. Factors affecting the relative abundance of the herbivore species in the dry season in Mpala

Model selection based on candidate models in Table 8, the multiple linear regressions between the explanatory variables and the RAI of the herbivore species as dependent variable shows that only one model was successfully and significantly explained the RAI of the herbivore species (AIC= -262.78, p<0.0001, Table 13). The RAI of the carnivore species and the RAI of the omnivore species are significant coefficients with a p value < 0.001. The RAI of the herbivore species is positively correlated with the RAI of the carnivore species, the RAI of the omnivore species, the distance to human settlement, the mean NDVI and the distance to river, but negatively correlated with the elevation, the RAI of human disturbance and the standard deviation of NDVI.

Table 13. The best prediction model for the analysis the RAI of the herbivore species in the dry season in Mpala

Predictor variable	Parameters estimate	P-value	Adjusted R^2
Intercept	1.48	0.062	
RAI of carnivore species*	3.6	<0.001	0.63
RAI of omnivore species*	2.7	<0.001	
Probability of human disturbance occurrence	0.07	0.13	
Distance to human settlement	3.08×10^{-5}	0.14	
Mean NDVI*	0.006	0.025	
Standard deviation of NDVI	-0.03	0.18	
Distance to river	1.52×10^{-4}	0.059	
Elevation*	-1.09×10^{-3}	0.026	

*variable included in the model with p<0.05

3.3. Spatial distribution of the mammal species diversity and abundance in the dry season in Mpala

Table 14. Parameters and statistics of semi-variogram models fitted for OK and RK

Variables	Model	Nugget variance	Total variance	Range(m)	SSErr	ME	RMSE
For ordinary kriging (OK)							
Mammal species richness	Spherical	0	0.45	3893	5.42×10^{-7}	-0.016	0.46
RAI of mammal species	Spherical	0.0045	0.0091	7825	7.27×10^{-9}	-0.00088	0.008
Carnivore species richness	Spherical	0.12	0.34	2859	1.26×10^{-6}	-0.0062	0.47
RAI of carnivore species	Exponential	0.002	0.0025	5672	1.27×10^{-10}	-4.66×10^{-5}	0.0027
Herbivore species richness	Spherical	0	4.73	3264	6.45×10^{-5}	-0.042	4.69
RAI of herbivore species	Spherical	0.015	0.007	6049	6.75×10^{-10}	-0.0013	0.005
For regression kriging using multiple regression (RK)	Spherical						
RAI of the mammal species (regression residuals)	Spherical	0	0.0052	2091	9.64×10^{-10}	-0.0085	0.0048
RAI of the carnivore species (regression residuals)	Spherical	0	0.0011	2176	1.23×10^{-11}	-0.00058	0.0015

3.3.1. Spatial distribution of the total mammal species diversity in the dry season in Mpala

After normalization, the spatial variation depicted by the semi-variogram model revealed a spatial structure in the mammal species richness (Table 14, for ordinary kriging). A spherical model fits the experimental semi-variogram well with less SSErr, and explained the spatial autocorrelation present in the model (Figure 15). The range is 3893 m.

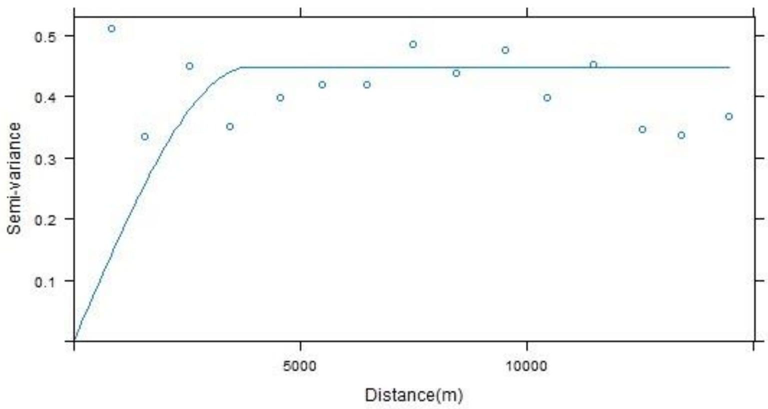

Figure 15. Variogram for mammal species richness

The ordinary kriging interpretation of mammal species richness is showed in Figure 16. Variance is lowest near sample points. Away from the area where samples were located the variance increases rapidly and reaches the variance of the datasets. The higher predictions are in the middle and south areas of Mpala (yellow points).

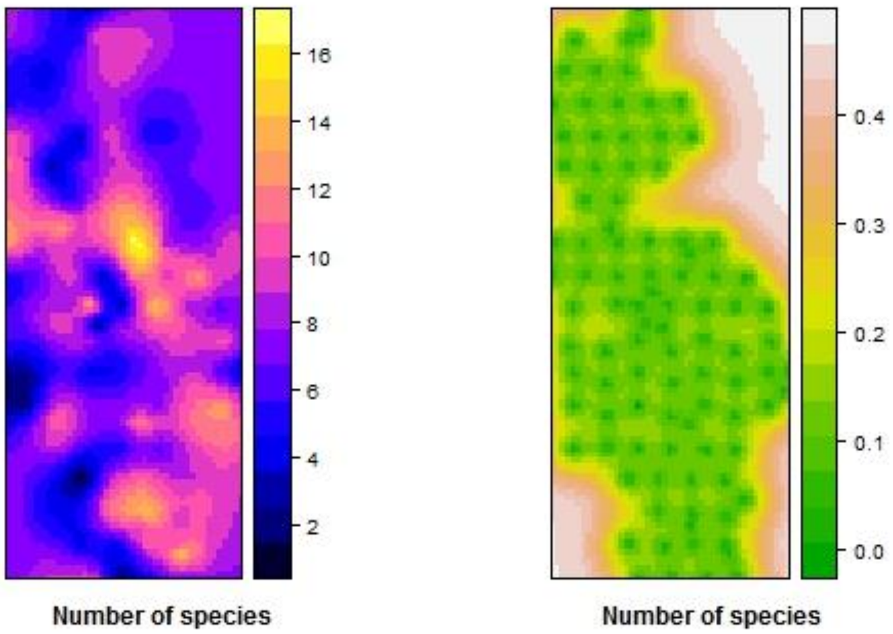

Figure 16. Spatial distribution of the total mammal species richness and the variance of prediction in the dry season in Mpala

3.3.2. Spatial distribution of the RAI of the mammal species in the dry season in Mpala

After normalization of RAI of the mammal species, the spatial variation depicted by the semi-variogram model revealed a spatial structure in the RAI of the mammal species (Table 14, for ordinary kriging). Among different fitting models, the spherical model fit the experimental semi-variogram well (Figure 17). The range is 7721m. The ordinary kriging interpretation of RAI of the mammal species is showed in Figure 18. In the southwest of Mpala, the prediction of probability of mammal species occurrence is lower.

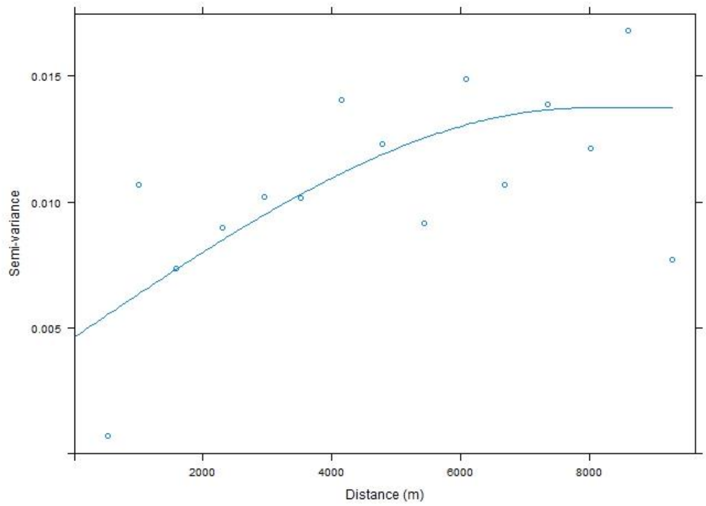

Figure 17. Variogram for the RAI of the mammal species

For regression kriging, based on the multiple regression considering spatial autocorrelation, the spatial variation depicted by the semi-variogram model revealed a spatial structure in the residuals of the RAI of the mammal species (Table 14, for RK using multiple regression). The result of model selection shows that the explanatory variables include the species richness of the mammal species, the elevation and the distance to river, have significant influence on the distribution of RAI of the mammal species. The spherical model fit the experimental semi-variogram well (Figure 19), and 50% structural variance was explained in the model. SSErr of variogram for regression kriging is less than that for ordinary kriging to predict the RAI of the mammal species. The distance of spatial dependence of the residual values between each camera station is 2091m. Figure 20 shows the distribution of RAI of the mammal species using multiple regression kriging.

For visualizing the difference between ordinary kriging and multiple regression kriging, the difference map used to show the difference of distribution of probability of mammal species occurrence in different method (Figure 21). There are no negative differences, i.e. RK > OK. The RK variance tend to be higher overall. The residual variogram has a lower sill than the ordinary variogram. Comparing OK and RK, RK's ME (-0.00085) is less than OK's ME (-0.00088) and is closer to 0. The RMSE of the RK (0.0048) is better than OK (0.0089).

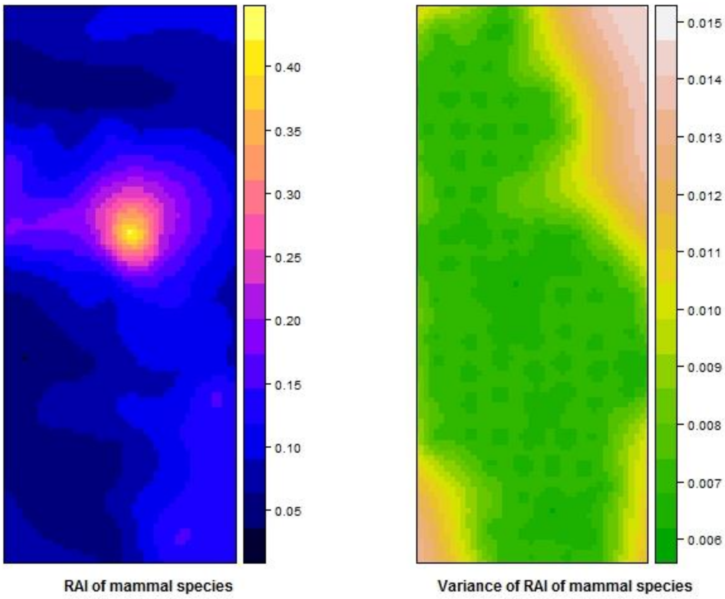

Figure 18. Spatial distribution of the mammal species abundance and prediction variance

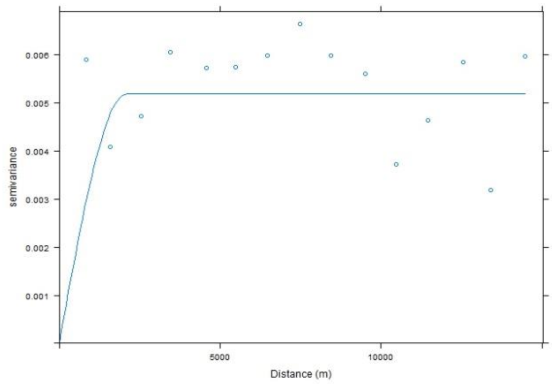

Figure 19. Variogram of RAI of mammal species with regression residuals

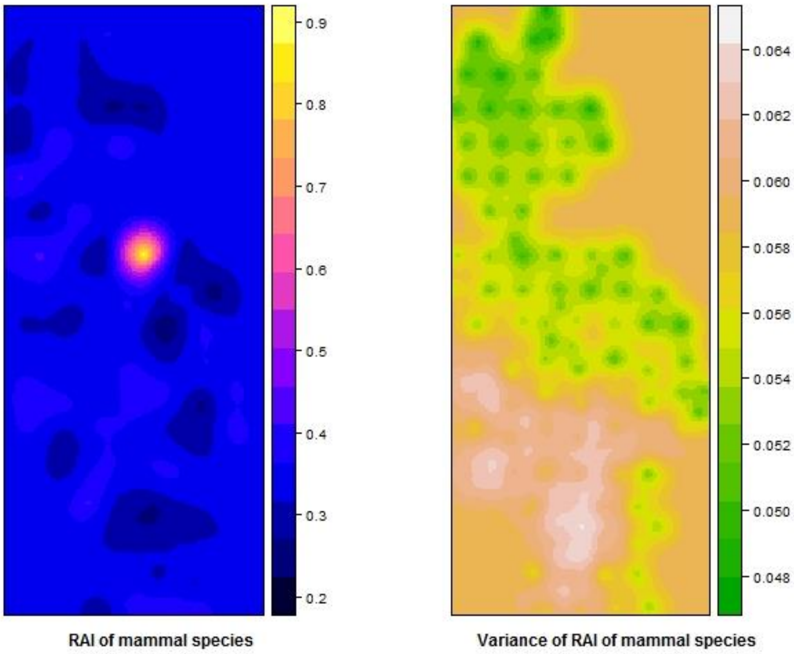

Figure 20. Regression kriging for spatial distribution of the mammal species abundance and variance of prediction

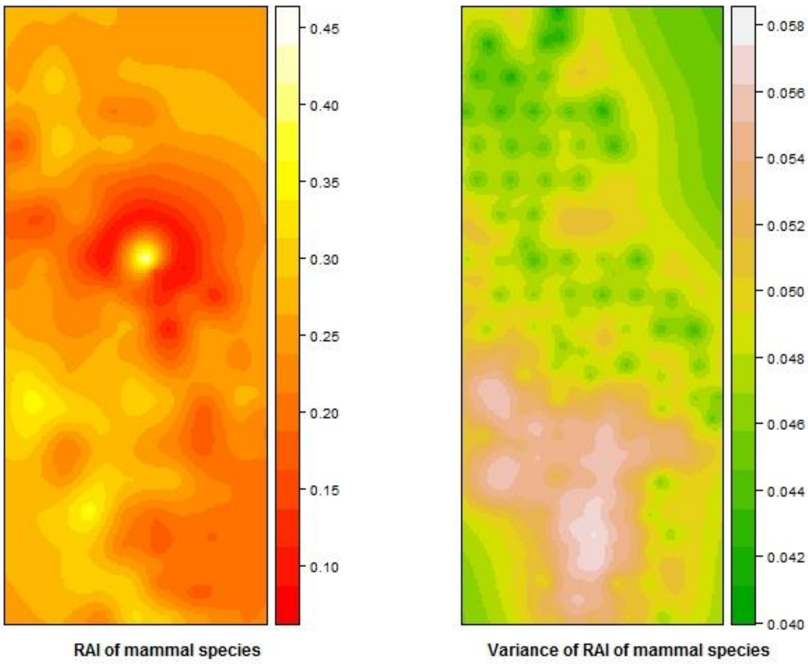

Figure 21. Difference map of RK-OK of the mammal species abundance and variance of difference map

3.3.2.1. Spatial distribution of the species richness of the carnivore species in the dry season in Mpala

The spatial variation depicted by the semi-variogram model revealed a spatial structure in the species richness of carnivore species (Table 14, for ordinary kriging). The spherical model fit well the experimental semi-variogram, and explained the spatial autocorrelation present in the model (Figure 22). The ordinary kriging interpretation is showed in Figure 23. The range is 2859m. The highest prediction of carnivore species richness is in the middle of Mpala (yellow points). There is a clear carve of lowest prediction from north to south.

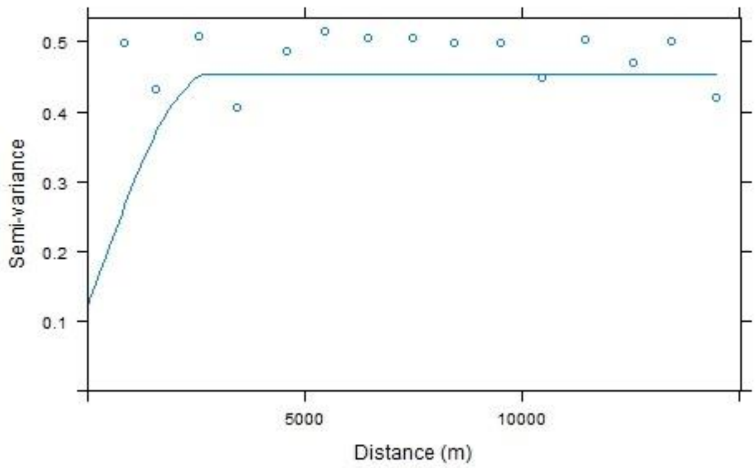

Figure 22. Variogram for the species richness of the carnivore species

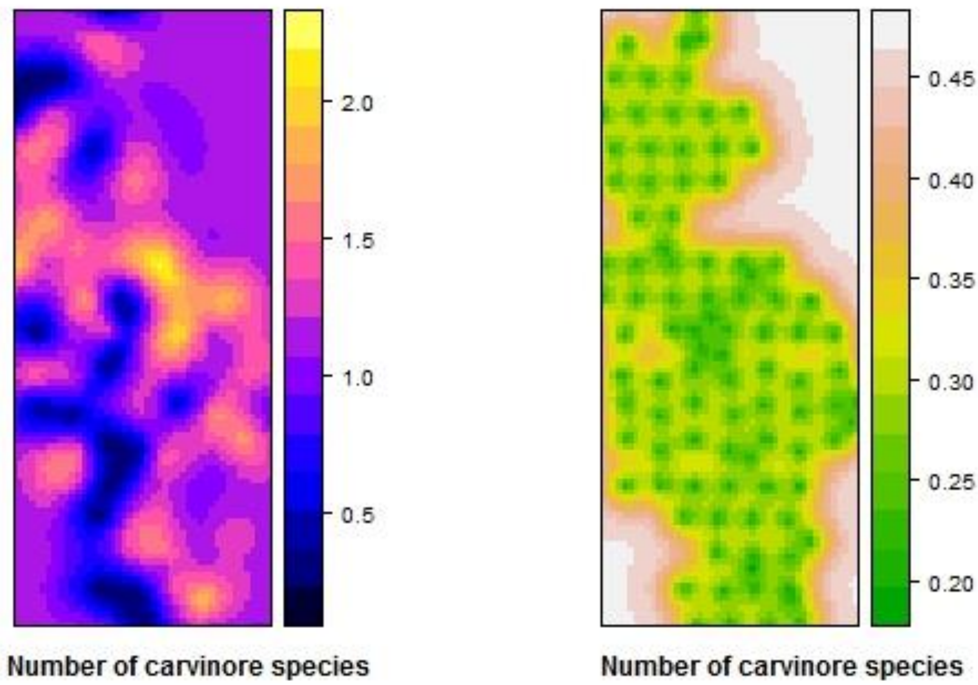

Figure 23. Spatial distribution of species richness of the carnivore species and the variance of prediction

3.3.2.2. Spatial distribution of the abundance of the carnivore species in the dry season in Mpala

The spatial variation depicted by the semi-variogram model revealed a spatial structure in the RAI of the carnivore species (Table 14, for ordinary kriging). Figure 24 shows the exponential model fits the experimental semi-variogram well, and explained the spatial autocorrelation. The range is 5672m. The ordinary kriging interpretation of RAI of carnivore species is showed in Figure 25. In the middle of Mpala, there is a “hot spot” with high RAI of carnivore species (yellow points). The lowest prediction is in the west area from north to south.

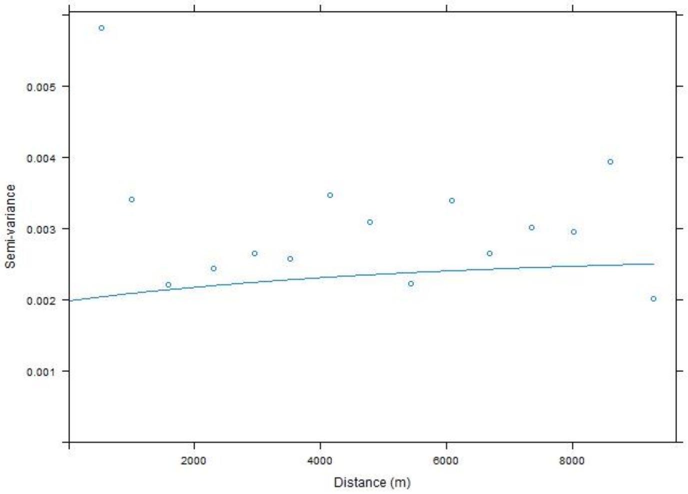

Figure 24. Variogram of the RAI of the carnivore species

For regression kriging, the result of model selection showed the explanatory variables including the RAI of the omnivore species, the RAI of the herbivore species, the probability of human disturbance occurrence, the woody coverage and the distance to river, have significant influence on the distribution of the RAI of the carnivore species. The spatial variation depicted by the semi-variogram model revealed a spatial structure in the residuals of the RAI of mammal species (Table 14, for RK using multiple regression). The spherical model fit the experimental semi-variogram well, and 57% structural variance was explained in the model. SSErr of variogram for regression kriging is less than that for ordinary kriging to predict the RAI of the carnivore species. The distance of spatial dependence of the residual values between each camera station is 2176m that is less than that of OK. Figure 26 shows the distribution of the RAI of the carnivore species using multiple regression kriging.

For visualizing the difference between ordinary kriging and multiple regression kriging, the difference map used to show the difference of distribution of RAI of carnivore species in different method (Figure 27). The RK variance tend to be higher overall, i.e. the difference RK-OK tends to be positive. Compared OK and RK, RK’s ME (-0.00058) is larger than OK’s ME (-4.66×10^{-5}). However, the RMSE of the RK (0.0015) is lower than OK (0.0027).

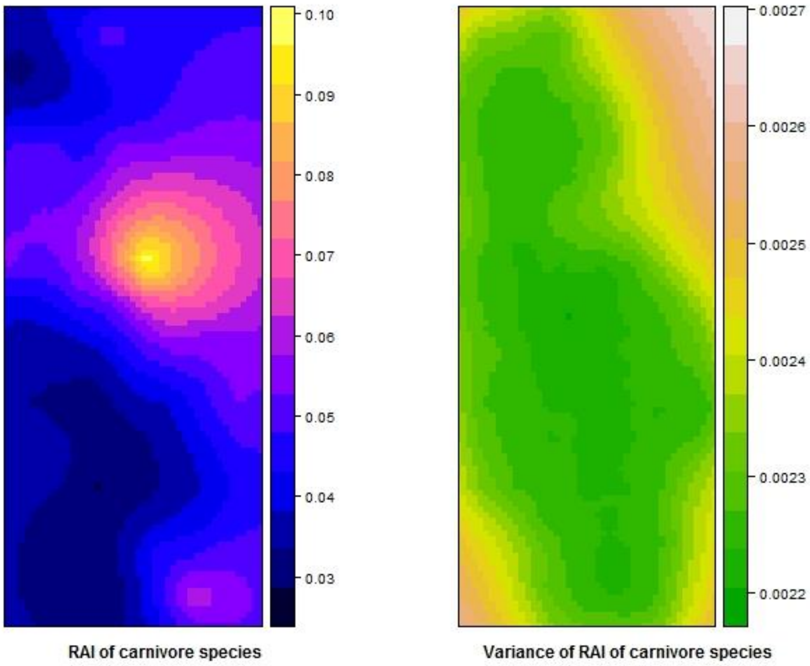

Figure 25. Spatial distribution of carnivore species abundance and the variance of prediction

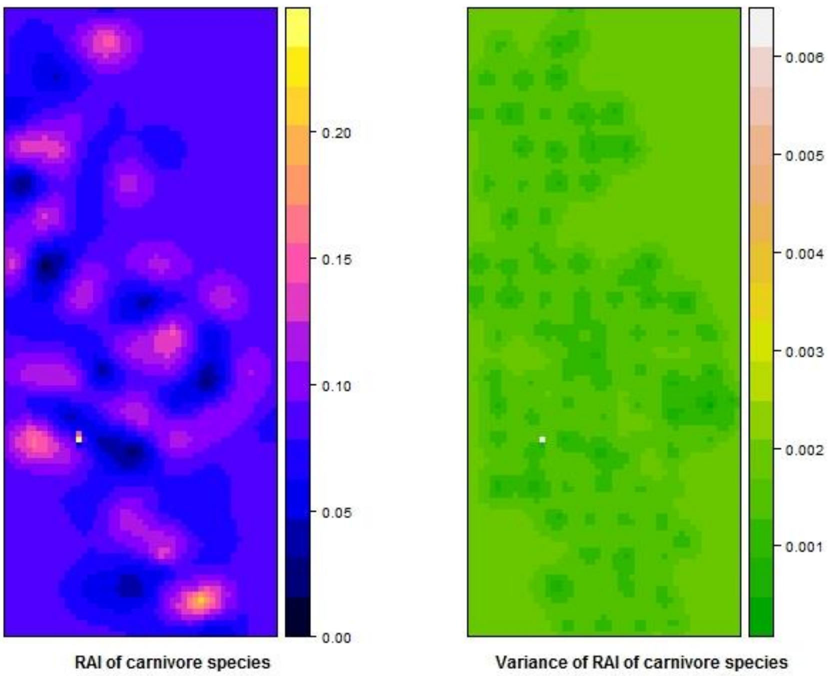

Figure 26. Regression kriging for spatial distribution of carnivore species abundance and the variance of prediction

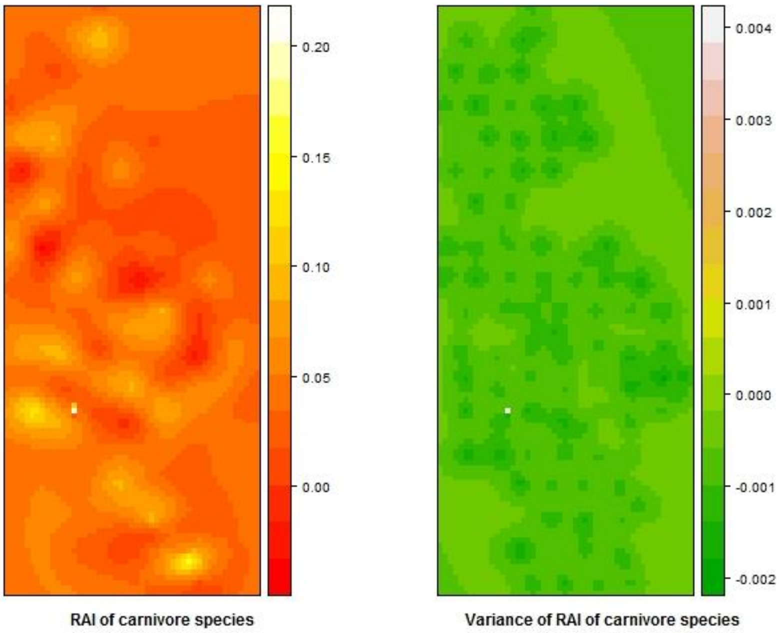

Figure 27. Difference map of RK-OK of the carnivore species abundance and the variance of difference

3.3.3. Spatial distribution of the herbivore species diversity and abundance in the dry season in Mpala

3.3.3.1. Spatial distribution of the species richness of the herbivore species in the dry season in Mpala

The spatial variation depicted by the semi-variogram model revealed a spatial structure in the herbivore species richness (Table 14, for ordinary kriging). The spherical model fits the experimental semi-variogram well, and explained the spatial autocorrelation present in the model (Figure 28). The ordinary kriging interpretation is showed in Figure 29. The range is 3264m. The highest prediction of carnivore species richness is in the south of the Mpala and some high prediction in the middle of the Mpala (yellow points).

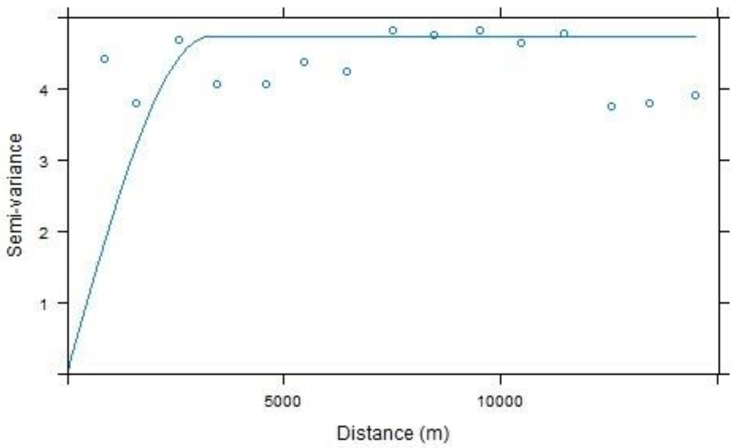

Figure 28. Variogram of the species richness of the herbivore species in the dry season in Mpala

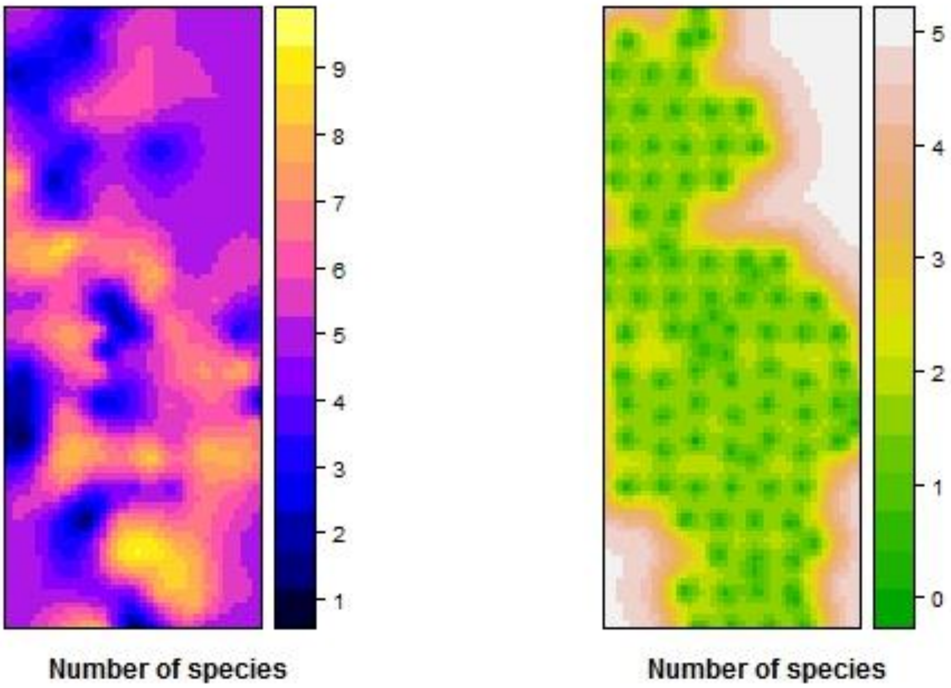

Figure 29. Spatial distribution of species richness of the herbivore species and the variance of prediction

3.3.3.2. Spatial distribution of the abundance of the herbivore species in the dry season in Mpala

The spatial variation depicted by the semi-variogram model revealed a spatial structure in the RAI of the herbivore species (Table 14, for ordinary kriging). Among different fitting models, the spherical model fits the experimental semi-variogram well, and explained the spatial autocorrelation present in the model (Figure 30). The range is 6565m. The ordinary kriging interpretation of the RAI of the herbivore species is showed in Figure 31. In the middle of Mpala, there is a "hot spot" with high the RAI of the herbivore species (yellow points). The lowest prediction is in the west area from north to south.

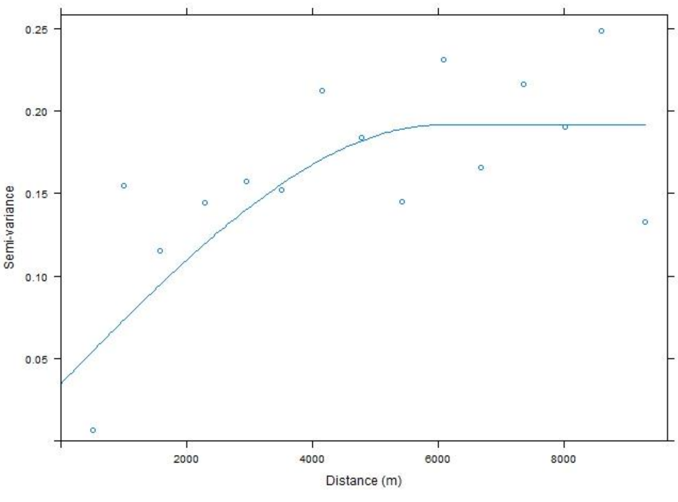

Figure 30. Variogram of the abundance of the herbivore species in the dry season in Mpala

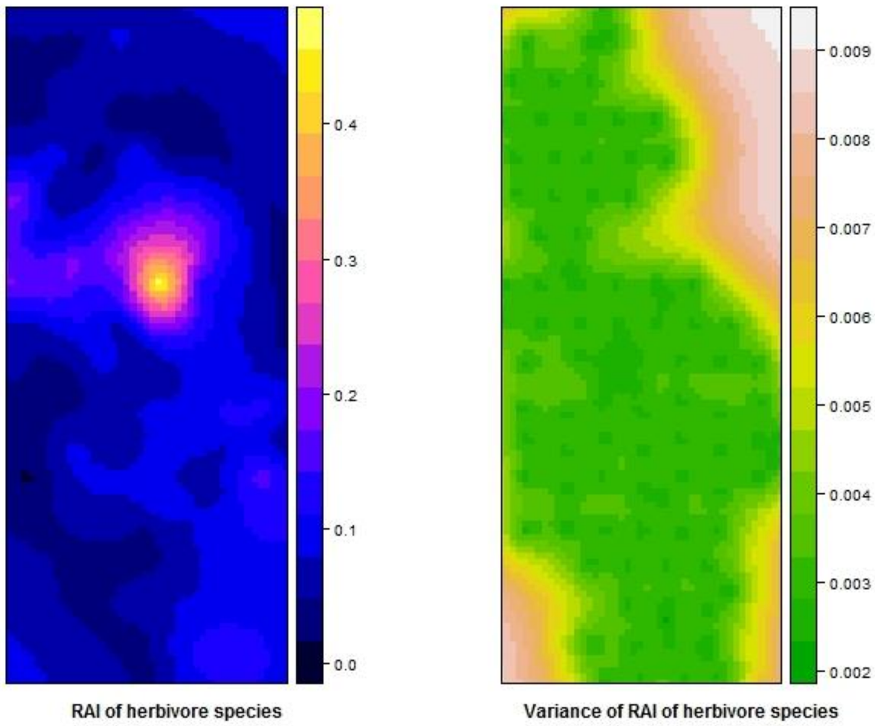

Figure 31. Spatial distribution of the RAI of the herbivore species and the variance of prediction

4. DISCUSSION

4.1. Factors significantly affecting the mammal species diversity and abundance in the dry season in Mpala

The multiple linear model analysis of environmental factors provided mechanistic insights about factors influencing mammal species diversity and abundance. Since humans can also cause changes in biodiversity, this study includes a variety of different human land use types (i.e. road, livestock and settlement). This will allow us to determine the importance of human-caused disturbance in altering mammal species diversity and abundance, as opposed to other factors such as elevation, or the inherent characteristics of the species present. There is no strong evidence shown that the livestock and human activities negatively affect the diversity and abundance of wildlife, compared to previous wildlife assessment studies in Kenya (Kinnaird & O'brien, 2012a). The possible reason is that Mpala is a living lab for conserving African wildlife in human-occupied landscapes. Bushmeat hunting is not allowed in this private land and there is no pastoral community as well as less tourism. So the human disturbance in this study area has no significant influence on the mammal species diversity and abundance. However, my data also showed that, the more human disturbance (including livestock-related activity and research activity), the less herbivore species abundance, but the larger carnivore species abundance. That confirms there is a competition of forage between herbivores and cattle (Sitters *et al.* 2009b), because livestock species have similar resource requirements to wild herbivores. So the competition between wildlife and livestock for forage resources will have influence on the distribution of mammal species diversity and abundance, because livestock species have similar resource requirements to wild herbivores. Furthermore, Muchiru et al., (2009) said increased herbaceous and woody species richness on abandoned settlements mirrors the increase in biomass. In the abandoned bomas, the palatable green grass and salt that remained on the soil are very attractive to herbivores in Mpala (fieldwork observation), which also has positive influence on the distribution of carnivore species.

For analysis of the food availability, I use NDVI as a surrogate of net primary productivity and woody coverage as a factor to estimate the woody cover. Aarrestad *et al.* (2011) thought that, at higher primary productivity, species richness and diversity decreases due to competitive exclusion. The previous statistical analyses revealed that higher average NDVI results in lower species richness in Kenya (Oindo & Skidmore, 2002). As was done in this study, this study has different result, because the type and form of relationship can very considerable in Mpala compared with the result at national scale. The model selection showed higher yearly average NDVI results in higher species richness of mammals, and whereas standard deviation of NDVI in dry season significantly have negative influence on the mammal species diversity. The high standard deviation of NDVI means larger variations in vegetation composition and growth. In additionally, Mpala is a dense scrub and open savanna habitat. The vegetation composition would determine the types of animal species, based on their feeding strategies. Oindo (2002) said vegetation quality has influence on herbivore diversity (because the rate of greening can be correlated with food quality). Based on the multiple regression result, the high interannual average NDVI increases herbivore species richness and RAI. The standard deviation of NDVI has significantly negative influence on RAI of herbivore species and the maximum NDVI in dry season has significantly negative influence on herbivore species diversity. This means the lager variation in vegetation growth in dry season results in low abundance and diversity of herbivore species (Oindo & Skidmore, 2002). However, the indices NDVI has no significant influence on carnivore species diversity and abundance. The woody coverage has no significant influence on the mammal species diversity and abundance.

Topography also has influence on the mammal species diversity in the dry season. From model selection, we can see the elevation and aspect have negative influence on the mammal species diversity. The elevation significantly affects the abundance of herbivore species. The higher of elevation, the less total mammal species abundance and herbivore species abundance. With the increase of elevation, there is less vegetation and the woody coverage is also less (fieldwork observation). Furthermore, the terrain has influence on the distribution of water, which affects the soil moisture. Since moisture availability determines plant production, forage availability declines with increasing productivity, and the abundance of herbivores will be limited by rainfall (Georgiadis *et al.,* 2007; Klop & Prins, 2008). However, this attempt is excluded from this study due to the inaccessibility of precipitation and temperature data, and this study focuses on the dry season. I assumed the probability of rainfall is almost 0 and there is no drought since 2009 (fieldwork observation).

The water accessibility during dry seasons is an important factor for structuring the distribution of mammal species abundance (Sitters *et al.*, 2009). It is known that water accessibility in dry seasons in savanna ecosystem negatively influence wild herbivore abundance. My data confirms this, the farther distance from a permanent river the lower the carnivore species abundance. Moreover, the distance to water pond had negative influence on the species richness of herbivore species. In the dry season, the herbivores must return to water to drink, the travel costs limited how far from water they can graze. Wildlife managers often set up permanent water supplies by creating artificial water points (Shannon *et al.*, 2009). However, the distance to river had positive correlation with total mammal species abundance and herbivore species abundance. Leeuw *et al.* (2001) discussed that because grazers have low drinking water requirements, they are able to remain in areas far from water, which appear to offer the highest forage quality. Gutu et al. (2010) also thought that the deterioration in vegetation conditions close to river forces animals to forage away from water.

Among environmental factors that significantly affect mammal species abundance, the interspecific competition plays an important role. The RAI of mammal species has high correlation with species richness. For carnivore species, the species richness of herbivore species and abundance of herbivore have significant influence on carnivore species richness and abundance. The herbivore species abundance is highly correlated with carnivore species abundance with a significant coefficients ($p < 0.001$). The abundance of herbivore species can explain 52% variability of carnivore species abundance. In additionally, the abundance of carnivore species and omnivore species has positive influence on the abundance of herbivore species with a significant coefficients ($p < 0.001$).

4.2. Spatial distribution patterns of the mammal species diversity and abundance in the dry season in Mpala

Modelling patterns of biodiversity at the species level is one of the most complex problems in ecology. This is because diversity is usually the outcome of many contributing factors whose relative importance varies with spatial and temporal scale. The continuous information concerning species distribution patterns is a limitation faced by mammal species conservation.

The spatial distribution detected in my study indicates that mammal species abundance in Mpala is significantly higher in central parts of the study area than in the north area. The significant relationship occurs between mammal species abundance and factors including species richness, elevation and distance to river. In the dry season, the water accessibility is an important factor structuring the distribution of mammal species abundance (Sitters *et al.*, 2009b). This area is near one permanent river with lower elevation and far from the area with human activity (field work observation). Additionally, the spatial distributions of carnivore species abundance and herbivore species abundance have the same "hot spot". That means the "hot spot" area is more attractive to herbivore species, which is also attractive to carnivore species. This area besides the permanent river has both high vegetation heterogeneity and food quantity (field work observation). Moreover, this study confirms that the higher environmental heterogeneity of an area the higher the herbivore species abundance (Leyequien *et al.*, 2007). Herbivores are sensitive to differences in vegetation characteristics across the area and tends to change the composition of vegetation increasing food resources availability (Leyequien *et al.*, 2007; Hagenah *et al.*, 2009). The food resources availability such as primary production, which is consumed by herbivores, which are themselves in turn consumed by carnivores. The local extirpation of large herbivores has consequences for entire ecosystems, because of their role in maintaining the diversity of predators and primary producers (N. Pettorelli *et al.*, 2010). The shrub damaged by elephant give more food to other small or median herbivores (fieldwork observation).

In this study, spatial distribution of mammal species diversity is more randomly compared with the distribution of mammal species abundance. The areas with high mammal species abundance also have high species richness. It is hard to determine the reason for spatial distribution of mammal species diversity because there is a spatial correlation between mammal species richness and abundance. Sitters *et al.* (2009b) indicate that livestock-related activity has interactions with wildlife distribution in African savannas through spatial partitioning. The results of my study did not show strong evidence that human disturbance, including livestock-related activity and research, has significant influence on spatial distribution of mammal species abundance. However, Mpala allow wide-ranging wildlife to move freely between different management systems on private land. Due to the lack of fencing, there are no edge effects in the distribution of mammal species diversity in Mpala (Mendes-oliveira *et al.*, 2012). After adding significant affecting factors, the spatial distribution of carnivore species abundance becomes more randomly-no more "hot spots".

Because I focused explicitly on mammal species diversity and abundance, my work had limitations. The model obtained in this study showed a large amount of unexplained variance. Firstly, I did not consider the body size of mammal species. The amount of consuming productivity is different for species with different body sizes. The mixed species groups affect the individual foraging success. The heterospecific group members may impose less competition for food than conspecific group members (Kiffner *et al.*, 2014). Secondly, the statistical association between mammal species richness and environmental factors may be misleading, owing to the dominating influence of common species compared to rare species (Burton *et al.*, 2012). It would be interesting to consider the body size and rareness of mammal species into the geostatistical modeling method. Thirdly, the south area of regression kriging prediction of carnivore species abundance has high variance compared with other areas. It could be interesting to add more samples in this area to have better model.

4.3. Modelling the spatial distribution patterns of mammal species diversity and abundance with camera trap data

Camera traps provided direct evidence to estimate the mammal species diversity and abundance in this study. Camera trapping is an efficient non-intrusive method compared to the traditional census (e.g. line transects) and is a popular method in ecology research recently. Due to using infrared motion sensors in camera traps, many nocturnal animals (e.g. carnivore) in the savanna can be detected under the same field sampling conditions. It will provide the high accuracy of species determinations, as well as the population structure and density (Joschko *et al.*, 2006; Bacaro *et al.*, 2011; Abi-Said & Amr, 2012; Bernard *et al.*, 2013; Ahumada *et al.*, 2011).

There are 42 kinds of mammal species including 17 kinds of carnivores and 20 kinds of herbivores detected by camera traps. The 9.0% of total photographic events is the carnivore species, which is less than that of herbivore species (85.3%). According to IUCN red list, the amount of photographic events of endangered species is 95 events including Wild dog and Grevy's zebra. 291 events are recorded the vulnerable species including Lion, Cheetah, Hippopotamus and Elephant. 78 events are recorded near threatened species including Striped hyena, Leopard and Beisa Oryx.

Furthermore, since the same animal can be counted more than once, the photographic rate of camera trap data can overestimate abundance (Silveira et al., 2003). However, this study focuses on large mammal species. Due to the movement of mammals, animal detections were considered independent if the time between consecutive photographs of the same species was more than 0.5 hours apart (O'Brien *et al.*, 2003;Park *et al.*, 2011).

In additionally, the systemic sampling procedure in this study provides relatively reliable data compared with the random sampling method. The random sampling method may present a biased sample yielding incomplete information if you were unable to access many portions of the region (Burton *et al.*, 2012). Furthermore, it is known that sample size affects the spatial pattern. Since the research of mammal species diversity needs repeated data, camera trapping method is useful, efficient, cost-effective, and easily replicable method to monitor study the overall mammal species diversity and abundance across Mpala. Despite the costs of camera traps, this method can be handled more easily and with relatively low costs in the long run (Silveira *et al.*, 2003).

4.4. Modelling the spatial distribution patterns of mammal species diversity and abundance with geostatistical method

By applying geostatistical models, well performing spatial distribution models were obtained for mammal species diversity and abundance. Less studies use geostatistical modelling method to model distribution of mammal species diversity and abundance based on the camera trap data. Due to the systemic sampling method, the maximum between each camera is 2 km, which is less than the range of every geostatistical model in this study. The range indicates that one would reasonably expect a spatial dependence between camera stations separated by this distance. So geostatistical modelling method can be successfully applied in Mpala based on camera trap data.

This study shows that regression kriging gives the higher prediction than ordinary kriging. This is because the standard errors of the multiple regression model coefficients introduce some uncertainty. Towards the edges, ordinary kriging has higher variance, because the standard errors of the linear model coefficients used in regression kriging are small, and the residual variogram has a lower sill than the ordinary variogram. Although this edge is far from observations, the lower sill keeps the prediction variance lower and this is only partly offset by the multiple linear model prediction variance. Cross-validation predictions showed that regression kriging's ME is less than ordinary kriging's ME and is more close to 0, which means there is less bias produced by model. The lower RMSE indicates that the accuracy of the regression kriging is better than ordinary kriging. In addition to providing more accurate continuous information for wildlife and habitat management, precise interpretation maps produced by geostatistical modeling can help to assess mammal species diversity and abundance response to global climate change.

My results are in line with findings of ecological spatial prediction, like mapping soil organic carbon (Simbahan, Dobermann, Goovaerts, Ping, & Haddix, 2006) and mapping tropical tree richness (Hernández-Stefanoni *et al.*, 2011), while these studies have found a better performances of regression kriging compared to ordinary kriging. There are two important implications from this study. Firstly, regression kriging can improve the accuracy of estimates of mammal species abundance by considering the spatial dependence within wildlife populations and incorporating with environmental variables. The second advantage is the flexibility of the regression model to explain the variability of the dependent variable. However, it must be stressed that the potential of regression kriging to improve estimations over ordinary kriging is high only if the associations between primary and ancillary variables are robust and significant (Simbahan *et al.*, 2006). Regression kriging performed better than ordinary kriging, demonstrating an improvement in the accuracy of estimations when using environmental factors for mammal species abundance prediction based on camera trap data.

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

The main objective of this study was to model the spatial distribution of mammal species diversity and abundance in Mpala savanna ecosystems from camera trap data using the geostatistical method. The results of this study demonstrated that camera trap data using systemic sampling method can be used to successfully predict the spatial distribution of mammal species diversity and abundance using ordinary kriging and regression kriging. The regression kriging can improve the accuracy of estimates of mammal species abundance by considering the spatial dependence within wildlife populations and incorporating with environmental variables. These mathematical models can inform conservation managers of making policies and practices for sustainable mammal species management.

This study also estimated the relationship between environmental factors and mammal species diversity and abundance based on camera trap data in Mpala. The multiple linear model analysis of environmental factors provided mechanistic insights about factors significantly influencing mammal species diversity and abundance. Among all the significant affecting factors, the interspecific competition plays an important role. The abundance of mammal species has high correlation with species richness. The abundance of herbivore species can explain 52% variability of carnivore species abundance. The herbivore species abundance is highly correlated with carnivore species abundance with a significant coefficients ($p < 0.001$). In additionally, the human disturbance in this study area has no significant influence on the mammal species diversity and abundance. My data also showed that, the topographic factors and water accessibility have negative influence on the mammal species diversity and abundance. The lager variation in vegetation growth in dry season results in low abundance and diversity of herbivore species, but the vegetation has no influence on abundance and diversity of carnivore species. Moreover, the woody coverage has no significant influence on the mammal species diversity and abundance.

The spatial distribution detected in my study indicates that mammal species abundance in Mpala is significantly higher in central parts of the study area than in the northern area. The spatial distributions of carnivore species abundance and herbivore species abundance have the same “hot spot”. That means the “hot spot” area is more attractive to herbivore species, which is also attractive to carnivore species. However, the spatial distribution of mammal species diversity is more randomly compared with the distribution of mammal species abundance. The areas with high mammal species abundance also have high species richness.

5.2. Recommendations

The mammal community is complicated, and models which reflect the characteristics and spatial distribution of mammal species and abundance are not able to fully explore the internal relationship of the environmental factors and mammal community. In order to further understand the relationship between the environment and distribution of mammal species diversity and abundance in the savanna ecosystem, it is suggested to choose some indicators for habitat heterogeneity analysis, like rainfall and the composition of vegetation. Considering the body size and rareness of species would give better understanding of the distribution of mammal species. However, the more indicators that are taken into consideration, the more complicated the model will be, which needs more time and cost for computation.

Spatial analysis of mammal species diversity and abundance helps us to better understand the ecosystem. The spatial model developed in this work could be seen as a tool for wildlife management: firstly, continues spatial predictions give the effective and valuable information for the research sampling design. Secondly, it is better to plan conservation strategies looking at the hotspots of high abundance of mammal species.

Furthermore, the combination of camera trap data with the geostatistical modelling method provides a more convenient and scientific continues information for mammal species conservation. This modeling approach is supposed to improve the accuracy of mammal species diversity and abundance mapping in other systems. The camera trap data collected in this study is restricted to the dry season, while it is better to integrate the information and build a database of the whole year. The difference between dry seasons and rainy seasons can help us learn more about the distribution of mammal species diversity and abundance as well as the change of mammal species distribution.

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APPEND IX

Table S1. Species identification (order, species common name and scientific name), body size (kg), IUCN red list.

Order	Family	Common Name	*Scientific Name*	HB(cm)	W(kg)	Class	Population Trend		IUCN red list
Aardvark	Aardvark	Aardvark	*Orycteropodidae*	100-158	40-82	O	Unknown	LC	http://www.iucnredlist.org/details/41504/0
Carnivore	Aardwolves	Aardwolf	*Proteles Cristata*	55-80	8-12	C	Stable	LC	http://www.iucnredlist.org/details/18372/0
Even-Toed Ungulates	Oxen	African Buffalo	*Syncerus Caffer*	170-340	250-850	H	Decreasing	LC	http://www.iucnredlist.org/details/21251/0
Even-Toed Ungulates	Hourse-Like Antelopes	Beisa Oryx	*Oryx Beisa*	153-170	116-209	H	Decreasing	NT	http://www.iucnredlist.org/details/15571/0
Carnivore	Dogs And Allies	Black-Backed Jackal	*Canis Mesomelas*	70-100	6.5-13.5	C	Stable	LC	http://www.iucnredlist.org/details/3755/0
Carnivore	Genets	Blotched Genet	*Genetta Tigrina*	40-55	1.2-3.1	C	Unknown	LC	http://www.iucnredlist.org/details/41702/0
Even-Toed Ungulates	Duiker	Bush Duiker	*Sylvicapra Grimmia*	70-115	11-25.5	H			http://www.catalogueoflife.org/col/details/species/id/19736057/common/62668
Even-Toed Ungulates	Sprial-Horned Bovines	Bushbuck	*Tragelaphus Scriptus*	105-150	24-80	H	Stable	LC	http://www.iucnredlist.org/details/22051/0
Carnivores	Cats	Cheetah	*Acinonyx Jubatus*	110-150	35-65	C	Decreasing	VU	http://www.iucnredlist.org/details/219/0
Carnivore	Genets	Common Genet	*Genetta Genetta*	40-55	1.3-2.25	C	Stable	LC	http://www.iucnredlist.org/details/41698/0
Even-Toed Ungulates	Pigs	Common Warthog	*Phacochoerus Africanus*	105-152	45-150	O	Stable	LC	http://www.iucnredlist.org/details/41768/0
Odd-Toed Ungulates	African Horses	Common Zebra	*Equus Quagga*	217-246	175-322	H	Stable	LC	http://www.iucnredlist.org/details/41013/0
Rodents	Porcupine	Crested Porcupine	*Hystrix Cristata*	60-100	12-25	H	Unknown	LC	http://www.iucnredlist.org/details/10746/0
Carnivore	Mongoose	Dwarf Mongoose	*Helogale Parvula*	18-28	0.02-0.04	C	Stable	LC	http://www.iucnredlist.org/details/41609/0
Even-Toed Ungulates	Sprial-Horned Bovines	Eland	*Tragelaphus Oryx*	200-280	300-942	H	Stable	LC	http://www.iucnredlist.org/details/22055/0
Proboscids	Elephant	Elephant	*Loxodonta Africana*	unstable measure	2,200-6,300	H	Increasing	VU	http://www.iucnredlist.org/details/12392/0
Even-Toed Ungulates	Giraffe	Giraffe	*Giraffa Camelopardalis*	3.5-4.8m	450-1930	H	Decreasing	LC	http://www.iucnredlist.org/details/9194/0
Even-Toed Ungulates	Gazelles	Grant'S Gazelle	*Gazella Granti*	140-166	38-81.5	H	Decreasing	LC	http://www.iucnredlist.org/details/8971/0
Even-Toed Ungulates	Sprial-Horned Bovines	Greater Kudu	*Tragelaphus Strepsiceros*	185-235	120-315	H	Stable	LC	http://www.iucnredlist.org/details/22054/0
Odd-Toed Ungulates	African Horses	Grevy'S Zebra	*Equus Grevyi*	250-300	350-450	H	Stable	EN	http://www.iucnredlist.org/details/7950/0
Even-Toed Ungulates	Dikdiks	Guenther'S Dikdik	*Madoqua Guentheri*	55-65	3.7-5.5	H	Stable	LC	http://www.iucnredlist.org/details/12669/0
Even-Toed Ungulates	Hippopotamus	Hippopotamus	*Hippopotamus Amphibius*	280-350	510-3,200	H	Decreasing	VU	http://www.iucnredlist.org/details/10103/0

Order	Family	Common Name	*Scientific Name*	HB(cm)	W(kg)	Class	Population Trend		IUCN red list
Even-Toed Ungulates	Alcelaphines,Topi And Allies	Impala	*Aepyceros Melampus*	120-160	40-80	H	Stable	LC	http://www.iucnredlist.org/details/550/0
Even-Toed Ungulates	Dwarfnantelopes	Klipspringer	*Oreotragus Oreotragus*	75-115	8-18	H	Stable	LC	http://www.iucnredlist.org/details/15485/0
Even-Toed Ungulates	Alcelaphines,Topi And Allies	Kongoni	*Alcelaphus Buselaphus*	160-215	116-218	H	Decreasing	LC	http://www.iucnredlist.org/details/811/0
Carnivores	Cats	Leopard	*Panthera Pardus*	104-190	28-90	C	Decreasing	NT	http://www.iucnredlist.org/details/15954/0
Carnivores	Cats	Lion	*Panthera Leo*	158-250	122-260	C	Decreasing	VU	http://www.iucnredlist.org/details/15951/0
Primates	Baboons	Olive Baboon	*Papio Anubis*	50-114	11-30	O	Increasing	LC	http://www.iucnredlist.org/details/40647/0
Hyrax	Hyraxes	Rock Hyrax	*Procavia*	38-60	1.8-5.5	H	Unknown	LC	http://www.iucnredlist.org/details/41766/0
Hares	True Hare	Scrub Hare	*Loxodonta Africana*	41-58	1.5-4.5	H	Increasing	VU	http://www.iucnredlist.org/details/12392/0
Carnivore	Cats	Serval Cat	*Felis Serval*	67-100	6-18	C	Stable	LC	http://www.iucnredlist.org/details/3755/1
Carnivore	Mongoose	Slender Mongoose	*Herpestes Sanguinea*	26-34	0.6-0.8	C	Stable	LC	http://www.iucnredlist.org/details/41606/0
Rodents	Ground Quirrels	Unstriped Ground Squirrel	*Xerus Rutilus*	20-26	0.03-0.04	O	Stable	LC	http://www.iucnredlist.org/details/23147/0
Carnivore	Hyaena	Spotted Hyaena	*Crocuta Crocuta*	100-180	40-90	C	Decreasing	LC	http://www.iucnredlist.org/details/5674/0
Even-Toed Ungulates	Dwarf Antelopes	Steinbuck	*Raphicerus Campestris*	70-95	7-16	H	Stable	LC	http://www.iucnredlist.org/details/19308/0
Carnivore	Hyaena	Striped Hyaena	*Hyaena Hyaena*	100-120	25-55	C	Decreasing	NT	http://www.iucnredlist.org/details/10274/0
Primates	Primates	Vervet Monkey	*Cercopithecus Pygerythrus*	38-62	3.5-8	O	Stable	LC	http://www.iucnredlist.org/details/136271/0
Even-Toed Ungulates	Reduncines,Kobs	Waterbuck	*Kobus Ellipsiprymnus*	177-235	160-300	H	Decreasing	LC	http://www.iucnredlist.org/details/11035/0
Carnivore	Mongoose	White-Tailed Mongoose	*Ichneumia Albicauda*	41-71	2-5.2	C	Stable	LC	http://www.iucnredlist.org/details/41620/0
Carnivore	Cats	Wild Cat	*Felis Silvestris*	45-73	3-6.5	C	Decreasing	LC	http://www.iucnredlist.org/details/8543/0
Carnivore	Dogs And Allies	Wild Dog	*Lycaon Pictus*	76-112	18-36	C	Decreasing	EN	http://www.iucnredlist.org/details/12436/0
Carnivore	Weasels'	Zorilla	*Ictonyx Striatus*	30-38	0.7-1.4	C	Stable	LC	http://www.iucnredlist.org/details/41646/0

EX	Extinct
EW	Extinct in the world
CR	Critically endangered /threatened
EN	Endangered
VU	Vulnerable
NT	Near threatened/ lower risk
LC	Least concern

Table S2. Correlation of variables

	sr	RAI_mammal	sr_omni	sr_herbi	sr_carni	RAI_carni	RAI_herbi	RAI_omni	RAI_human	NDVI_mean	NDVI_std	NDVI_min	NDVI_max
sr	1	0.7	0.47	0.85	0.77	0.67	0.69	0.44	-0.02	-0.13	-0.13	-0.04	-0.16
RAI_mammal	0.7	1	0.5	0.48	0.58	0.78	0.99	0.76	-0.11	-0.18	-0.04	-0.08	-0.13
sr_omni	0.47	0.5	1	0.16	0.24	0.41	0.45	0.7	-0.02	-0.19	0.06	-0.13	-0.02
sr_herbi	0.85	0.48	0.16	1	0.4	0.31	0.51	0.17	0.01	0.02	-0.18	0.07	-0.11
sr_carni	0.77	0.58	0.24	0.4	1	0.81	0.55	0.32	-0.05	-0.2	-0.07	-0.1	-0.17
RAI_carni	0.67	0.78	0.41	0.31	0.81	1	0.72	0.63	0.01	-0.17	0.03	-0.09	-0.08
RAI_herbi	0.69	0.99	0.45	0.51	0.55	0.72	1	0.69	-0.13	-0.16	-0.05	-0.07	-0.13
RAI_omni	0.44	0.76	0.7	0.17	0.32	0.63	0.69	1	-0.05	-0.19	0.04	-0.1	-0.06
RAI_human	-0.02	-0.11	-0.02	0.01	-0.05	0.01	-0.13	-0.05	1	0.13	-0.02	0.14	0.05
NDVI_mean	-0.13	-0.18	-0.19	0.02	-0.2	-0.17	-0.16	-0.19	0.13	1	0.26	0.64	0.74
NDVI_std	-0.13	-0.04	0.06	-0.18	-0.07	0.03	-0.05	0.04	-0.02	0.26	1	-0.34	0.68
NDVI_min	-0.04	-0.08	-0.13	0.07	-0.1	-0.09	-0.07	-0.1	0.14	0.64	-0.34	1	0.35
NDVI_max	-0.16	-0.13	-0.02	-0.11	-0.17	-0.08	-0.13	-0.06	0.05	0.74	0.68	0.35	1
NDVI_max_dry	-0.19	-0.17	-0.2	-0.07	-0.18	-0.14	-0.16	-0.19	0.13	0.92	0.14	0.71	0.7
NDVI_std_dry	-0.24	-0.08	0.01	-0.3	-0.11	-0.02	-0.09	-0.03	-0.12	0.36	0.74	-0.16	0.67
NDVI_min_dry	-0.04	-0.1	-0.15	0.08	-0.11	-0.11	-0.09	-0.11	0.17	0.65	-0.35	0.98	0.33
NDVI_max_dry	-0.22	-0.11	0	-0.24	-0.13	-0.06	-0.12	-0.06	-0.05	0.51	0.59	0.21	0.78
distance_human	0.07	0.08	-0.14	0.08	0.14	0.04	0.09	-0.03	-0.06	0.07	0.11	0	0.14
distance_boma	-0.11	-0.02	0.11	-0.18	-0.06	-0.04	-0.02	0.06	-0.23	-0.14	0.1	-0.07	0.06
Elevation	-0.14	-0.23	-0.28	0.05	-0.22	-0.25	-0.22	-0.2	0.18	0.57	-0.15	0.37	0.14
woody coverage	0.05	0.01	0.03	0.08	-0.01	-0.07	0.02	0	0.01	0.11	-0.22	0.2	0.02
Aspect	-0.04	0.05	0.05	-0.08	0	0.05	0.06	0.02	0.09	-0.11	-0.03	-0.06	-0.06
distance_river	-0.13	-0.04	-0.1	-0.07	-0.14	-0.16	-0.01	-0.11	-0.01	0.1	0.06	-0.01	0.01
Slope	-0.11	-0.11	-0.03	-0.08	-0.12	-0.14	-0.11	-0.05	0.1	0.16	-0.16	0.2	-0.01
distance_water pond	0.07	0.17	0.24	-0.11	0.16	0.22	0.15	0.19	-0.1	-0.18	0.09	-0.11	-0.04
distance_road	-0.09	-0.11	-0.02	-0.06	-0.1	-0.07	-0.13	-0.01	0.05	-0.13	-0.14	-0.08	-0.23

	NDVI_mean_dry	NDVI_std_dry	NDVI_min_dry	NDVI_max_dry	distance_human	distance_boma	Elevation	woody coverage	Aspect	distance_river	Slope	distance_water	distance_road
sr	-0.19	-0.24	-0.04	-0.22	0.07	-0.11	-0.14	0.05	-0.04	-0.13	-0.11	0.07	-0.09
RAI_mammal	-0.17	-0.08	-0.1	-0.11	0.08	-0.02	-0.23	0.01	0.05	-0.04	-0.11	0.17	-0.11
sr_omni	-0.2	0.01	-0.15	0	-0.14	0.11	-0.28	0.03	0.05	-0.1	-0.03	0.24	-0.02
sr_herbi	-0.07	-0.3	0.08	-0.24	0.08	-0.18	0.05	0.08	-0.08	-0.07	-0.08	-0.11	-0.06
sr_carni	-0.18	-0.11	-0.11	-0.13	0.14	-0.06	-0.22	-0.01	0	-0.14	-0.12	0.16	-0.1
RAI_carni	-0.14	-0.02	-0.11	-0.06	0.04	-0.04	-0.25	-0.07	0.05	-0.16	-0.14	0.22	-0.07
RAI_herbi	-0.16	-0.09	-0.09	-0.12	0.09	-0.02	-0.22	0.02	0.06	-0.01	-0.11	0.15	-0.13
RAI_omni	-0.19	-0.03	-0.11	-0.06	-0.03	0.06	-0.2	0	0.02	-0.11	-0.05	0.19	-0.01
RAI_human	0.13	-0.12	0.17	-0.05	-0.06	-0.23	0.18	0.01	0.09	-0.01	0.1	-0.1	0.05
NDVI_mean	0.92	0.36	0.65	0.51	0.07	-0.14	0.57	0.11	-0.11	0.1	0.16	-0.18	-0.13
NDVI_std	0.14	0.74	-0.35	0.59	0.11	0.1	-0.15	-0.22	-0.03	0.06	-0.16	0.09	-0.14
NDVI_min	0.71	-0.16	0.98	0.21	0	-0.07	0.37	0.2	-0.06	-0.01	0.2	-0.11	-0.08
NDVI_max	0.7	0.67	0.33	0.78	0.14	0.06	0.14	0.02	-0.06	0.01	-0.01	-0.04	-0.23
NDVI_max_dry	1	0.42	0.72	0.6	0.1	-0.05	0.46	0.17	-0.05	0.1	0.23	-0.18	-0.14
NDVI_std_dry	0.42	1	-0.18	0.86	0.1	0.22	-0.1	-0.02	-0.04	0.09	-0.02	0.09	-0.15
NDVI_min_dry	0.72	-0.18	1	0.18	-0.03	-0.09	0.4	0.23	-0.09	-0.04	0.24	-0.12	-0.07
NDVI_max_dry	0.6	0.86	0.18	1	0.14	0.28	-0.1	0.06	-0.07	-0.03	0.03	0.07	-0.2
distance_human	0.1	0.1	-0.03	0.14	1	0.12	0.19	-0.1	0.01	0.2	0.03	-0.25	0
distance_boma	-0.05	0.22	-0.09	0.28	0.12	1	-0.31	0.14	-0.05	-0.16	0.27	0.19	0.01
Elevation	0.46	-0.1	0.4	-0.1	0.19	-0.31	1	-0.07	-0.09	0.4	0.11	-0.42	0.09
woody coverage	0.17	-0.02	0.23	0.06	-0.1	0.14	-0.07	1	0	-0.26	0.3	0.06	-0.2
Aspect	-0.05	-0.04	-0.09	-0.07	0.01	-0.05	-0.09	0	1	0.19	-0.12	-0.28	0.02
distance_river	0.1	0.09	-0.04	-0.03	0.2	-0.16	0.4	-0.26	0.19	1	0.03	-0.15	0.08
Slope	0.23	-0.02	0.24	0.03	0.03	0.27	0.11	0.3	-0.12	0.03	1	-0.08	0.13
distance_water pond	-0.18	0.09	-0.12	0.07	-0.25	0.19	-0.42	0.06	-0.28	-0.15	-0.08	1	-0.1
distance_road	-0.14	-0.15	-0.07	-0.2	0	0.01	0.09	-0.2	0.02	0.08	0.13	-0.1	1