

**Safari Science: Testing the Feasibility and Reliability of Tourists as Citizen Scientists in
East African Protected Areas**

By

Cara Elizabeth Steger

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Committee:

Assistant Professor Bilal Butt, Chair

Associate Professor Ines Ibáñez

Abstract

Wildlife populations continue to decline in East Africa, both in and around Protected Areas (PAs). High quality data on the density and distribution of wildlife are essential for effective conservation and management. However, methods that accurately capture data on wildlife locations at fine scales over large land areas have proven to be prohibitively difficult, expensive and time-consuming given the logistical and financial constraints of East African PAs. This study explores whether citizen science can be a reliable alternative to conventional methods of wildlife monitoring.

Citizen science (CS) – also known as public participation in data gathering – has the potential to answer questions that have long plagued conservation scientists, as it has been shown to decrease monitoring costs while increasing public engagement in conservation issues. Despite the growing use of CS in ecological research, debates persist over the reliability of these datasets. An early and continuing concern of CS data is the effect of observer error, which if ignored can produce misleading ecological conclusions in modeled species-environment relationships.

Through the implementation of a pilot program, I address the feasibility, reliability, and utility of CS for wildlife management in East African PAs. I ask (i) what problems and prospects arise when attempting to implement a CS program in East Africa? (ii) can the data generated from this method approximate the quality and quantity of data from more conventional sampling techniques?, and (iii) can CS data be *useful* for wildlife managers?

To test these questions, this study uses two independent methods to gather spatial and demographic data on twenty-nine species within a private conservancy in southwestern Kenya. In method 1, I asked tourists to gather data on wildlife during their game drives. The novel use of mobile technology aided my ability to enter and manage data quickly, though this study is limited by a lack of volunteer interest and motivation. I report several observations regarding the potential for future CS programs in the region, finding a need for PA administration to take ownership over program and data management. In reality, the large amount of time needed to organize and implement CS programs on a daily basis severely restricts the potential for CS in small East African PAs, as lodge managers have little time, inclination, and resources to devote to these programs.

Method 2 uses line transects, a conventional ecological sampling technique, providing a validation dataset for testing the reliability of CS data. I use generalized linear models (GLMs) to model the species-environment relationships for nine commonly reported species, as it is a common analytical technique used by ecologists and wildlife managers for ecological inference. I find SS data performed reasonably well for eight out of nine species, with accuracies ranging from 60-87%. However, these results are complicated by high uncertainty in model performance and ecological validity, thus limiting the usefulness of this data for management and conservation planning. I find GLMs are not the best methods for analyzing CS data as they lack the capacity to account for observer error, an important source of bias in CS datasets. When this error is sufficiently accounted for, CS data could be much more reliable for ecological inference by wildlife managers.

In conclusion, I find citizen science to be a complex and difficult monitoring method, both logistically and analytically challenging. Though there is great potential for CS in East African PAs, substantial barriers exist and impede successful program establishment. I recommend future programs in East Africa carefully and realistically weigh their ability to address these obstacles before implementing a Safari Science approach to monitoring wildlife.

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Chapter One | Introduction

This thesis evaluates the potential for citizen science-based animal monitoring in a protected area in southwestern Kenya, exploring the feasibility, reliability and utility of citizen science (CS) methods. It is motivated by the need for improved ecological monitoring in East African savannas, as evidenced by the dramatic loss of endemic wildlife seen over the past several decades. Within broader themes of biodiversity loss, protected areas management, and safari tourism, I investigate the challenge of fine-scale animal monitoring by volunteers. Using a small, private conservancy as my case study, I pursue three main objectives (i) assess the potential for a CS monitoring program, (ii) evaluate the accuracy of CS data, and (iii) examine the value of fine-scale, CS-derived data for management decisions.

Biodiversity in Protected Areas

Despite some localized successes, global biodiversity loss does not appear to be slowing (Butchart et al. 2010). In an effort to counter these losses, as many as 100,000 Protected Areas (PAs) have been created, covering approximately 12.9% of the Earth's terrestrial ecosystems (Chape et al. 2005; Ervin 2011). PAs are an integral element of global conservation models (Caro 2011), yet financial support for even basic monitoring infrastructure is lacking in 60% of the PAs studied recently by Leverington et al. (2010). The rate of PA establishment has perhaps exceeded the capacity to monitor the species populations they exist to protect (Chape et al. 2005), as researchers report many PAs with inadequate design and coverage that lack the infrastructure necessary to address growing environmental threats such as climate change (Ervin 2003). Issues with management effectiveness are strongly tied to a lack of data; scientists have very little detailed and quantitative information on the numerous components of threatened ecosystems (Balmford et al. 2005), and efforts need to be made to increase monitoring at appropriate temporal and spatial scales (Dobson 2005). Quantification of species-environment relationships through the empirical modeling of fine-scale animal monitoring data can potentially shed light on the mechanisms behind wildlife declines (Guisan and Zimmermann 2000).

Modeling the Species-Environment Relationship

Conservation ecology increasingly depends on multivariate, spatially explicit models with some level of ecological realism to understand animal distributions and habitat preferences (Hirzel et al. 2002). Predictive modeling is a cost-effective method when it interpolates data from expensive and time consuming field surveys (Franklin 1995; Imam et al. 2009; Ogutu et al. 2006). Spatially-interpolated landscape variables like topography and habitat are necessary for quantifying the species-environment relationship (Franklin 1995), as these models are based on various hypotheses as to how environmental or topographic factors influence the distribution of species and communities (Guisan and Zimmermann 2000; Mackey and Lindenmeyer 2001; Millington et al. 2010; Paudel et al. 2012). Detailed understanding of species landscape preferences can be used in the creation of ecologically-sound and robust conservation plans, increasing managers' abilities to address key environmental and human variables in the landscape (Ferrier et al. 2002; Franklin 1995; Imam et al. 2009; Ogutu et al. 2006; Millington et al. 2010).

It is admittedly difficult to model the environmental relationships of mobile species, as they use resources in a temporally variable manner in often spatially heterogeneous landscapes (Elith and Leathwick 2009). However, the benefits of successful attempts can significantly improve manager's understanding of species-specific preferences for landscape patterns, aiding in the development of robust and ecologically validated conservation management plans (Elith et al. 2006; Ferrier et al. 2002; Fleishmann et al. 2001). Unfortunately, evidence of the practiced use of these models in real-world conservation is still minimal, and the field would benefit from a better integration of theory, concepts, and practice (Elith and Leathwick 2009; Guisan et al. 2013). One of the challenges for the development of such models is the acquisition of fine-scale spatial data on wildlife locations, as this can be a costly and complicated process.

The Challenge of Monitoring

Wildlife declines in East Africa are particularly drastic, with estimates as high as 80% since the mid-1970s – both within and around Protected Areas (Craigie et al. 2010; Homewood et al. 2001; Ogotu et al. 2011). The declines of endemic East African species have been studied for some time now, but researchers differ on the primary drivers of the phenomena. Theories emphasize habitat loss or modification (largely due to mechanized agriculture), increased livestock grazing, hunting, drought and disease as potential factors, but firm conclusions are problematic given the paucity of data at fine spatial and temporal scales (Butt and Turner 2012; Homewood et al 2001; Odadi et al. 2011; Thompson and Homewood 2004; Serneels, Said, and Lambin 2001).

Information related to biodiversity changes in East African savannas is critical to assess the trend and to develop adequate conservation plans (Ferrier et al. 2002; Funk and Richardson 2002; Rushton et al. 2004; Ogotu et al. 2006). However, methods that accurately capture data on wildlife locations at fine scales over large land areas have proven to be prohibitively difficult, expensive and time-consuming given the financial and logistical constraints of East African PAs (Lung and Schaab 2010; Witmer 2005). There are 39 National Parks in Kenya and Tanzania, making up 33% of these countries' landmass (KWS 2014; TANAPA 2014). The available manpower, and the financial support to train and outfit them, is simply not sufficient to monitor this large land area effectively. For example, 400 rangers are tasked with patrolling 42,000 square kilometers of rough terrain in Tsavo Conservation Area in Kenya (Mwadime 2012). With strong international pressure to end poaching in the region, those rangers have little time or resources left to conduct scientific monitoring of wildlife populations themselves.

Other more feasible approaches to monitoring are not particularly precise and can be highly biased. For example, aerial flight monitoring is a popular method for estimating wildlife populations in East Africa (Bhola et al. 2012b), but these methods are expensive and only feasible in open habitats during clear weather conditions (Caughley and Sinclair 1994; Ericsson and Wallin 1999; Singh and Miller-Gulland 2011). There remains a need for high quality data on the density and distribution of wildlife, to guide managers' decisions on the allocation of limited resources (Ferrier et al. 2002; Funk and Richardson 2002; Rushton et al. 2004; Ogotu et al. 2006).

Growing Potential for Citizen Science

Although there is an increasing range and volume of public voices interested in advancing conservation efforts, ecological issues often fall short of mainstream discussion and little political will exists to support these efforts. Having failed to meet the Millennium Development Goals' objective of reducing the rate of biodiversity loss by 2010 (Adenle 2012), future conservation

research must strive to identify potential methods for improved wildlife monitoring, particularly in species-rich and economically constrained developing countries.

Citizen science – also known as public participation in scientific research – has the potential to address monitoring issues in East African wildlife management, as it has been shown to decrease monitoring costs while increasing public engagement in conservation issues (Bonney et al. 2009; Danielsen et al. 2005; Darwall and Dulvy 1996). A classic example of CS is the Christmas Bird Count, a nation-wide event that began in 1900 and continues today, sponsored by the National Audubon Society (Silvertown 2009). The past decade has seen a rise in CS projects, ranging from local to global scales, engaging hundreds of thousands of volunteers, and describing and recording an incredible range of taxa. Volunteers gain experience in scientific thinking and methods, and generally gain a greater appreciation for nature and conservation (Cohn 2008; Price and Lee 2013). The first model for CS program development was published in 2009, and many web-based tools for data-entry infrastructure and guidance have arisen since then (Bonney et al. 2009; Dickinson et al. 2012). From 2008 to 2010 alone, the number of CS projects on record at Cornell's Lab of Ornithology rose from 200 to over 600 (Cohn 2008; Dickinson et al. 2010).

In 2012, two major advances occurred in the citizen science community: the first Conference on Public Participation in Scientific Research in Portland, Oregon, and the first journal issue with exclusively CS-themed content released by *Frontiers in Ecology and the Environment*. Annual citations for articles with a CS theme are approaching 4,000, according to the Web of Science citation report (Figure 1). The relevance and reliability of CS is becoming increasingly accepted in global conservation circles. Though mainly focused in North America and the UK, CS programs are slowly expanding into developing countries - providing a monitoring method that offers a way to maximize the benefits and minimize the costs of conservation initiatives.

Testing the Reliability of Citizen Science Data

The benefits of CS are well-published and worthy of the attention given (Bonney et al. 2009; Cohn 2008; Dickinson et al. 2010), but there is a startling lack of research concerning the quality and reliability of CS datasets. Though observer ability was an early concern for CS researchers, it is not yet clear what the best methods are to address it (Dickinson et al. 2010). In 2005, Danielsen et al. 2005 found just 16 published comparisons of CS data with traditionally sampled (TS) data, only four of which occurred in a developing country. These numbers have increased slightly over the years, and describe some encouraging results, but many scientists remain skeptical that CS can produce data that are useful for management or research (Danielsen et al. 2005; Penrose and Call 1995). This opinion is supported by research that shows CS datasets have higher variability than those collected by trained scientists (Ericsson and Wallin 1999), particularly when it comes to estimating species abundance (Foster-Smith and Evans 2003; Genet and Sargent 2003).

Effects of site, year, and observer bias are common in ecological studies, resulting in correlations of the response variable within groups of shared characteristics (Tonachella et al. 2012). Observer variability in wildlife surveys may arise from variation in volunteers' level of experience or motivation (Moyer-Horner et al. 2012), and can be influenced by characteristics such as gender, age, fitness, or interest/boredom (Buesching et al. 2014; Foster-Smith and Evans 2003). The quantification of these observer effects is an important, and growing, concern amongst CS researchers. When observer bias can be accounted for in modeling CS data, it improves the utility of the data (Hochachka et al. 2012; Moyer-Horner et al. 2012; Tonachella et al. 2012). Considerable

work remains to be done in proving the utility of hierarchical and mixed methods models for explaining this type of variation.

Studies indicate that proper sampling design and training of volunteers can potentially minimize sources of error in CS datasets while maintaining high utility of the data (Bhattacharjee 2005; Darwall and Dulvy 2003; Foster-Smith and Evans 2003; Yoccoz et al. 2003). Recently, scholars have focused on data cleaning and data improvement technologies post-collection, such as “trust metrics” to filter out questionable data sources (Hunter et al. 2013; Newman et al. 2012). These a posteriori corrections should not replace in situ, direct comparisons of CS and TS data, as these studies yield the most reliable estimates of the accuracy of CS data. Most recently, CS data have been tested against TS data for (i) modeling owl habitat in eastern US woodlands (Nagy et al. 2012), (ii) counting pika in the mountains of Montana (Moyer-Horner et al. 2012), and (iii) counting sharks in Pacific coral reefs (Vianna et al. 2014). In most of these studies, CS data has been judged generally reliable, and approved for use in management decision-making. However, those scholars have been careful to emphasize the need for future research, especially in site-specific contexts, to ensure CS data are credible, precise, and reliable (Vianna et al. 2014).

Thesis Outline

This thesis is the first to test the reliability of CS data from tourists in an East African savanna context, thus adding to the growing reservoir of knowledge surrounding CS wildlife monitoring.

I begin in Chapter Two by addressing the question: what kinds of problems and prospects are presented when attempting to implement a CS monitoring method in East Africa? Engaging mobile devices with existing safari tourism infrastructure, I elaborate on the problematic term “citizen” in this context, issues relating to data quality and quantity, the scalability and transferability of our “Safari Science” program. Recognizing CS as a potentially useful and effective tool in East African Protected Areas management, I describe some significant barriers to the establishment of sustainable, productive CS monitoring programs. I find that ownership over the program and the data produced by it must come from within the host organization if CS is to have any success there.

Chapter Three investigates the accuracy of CS data, comparing it to a dataset gathered using traditional ecological sampling techniques. As CS methods continue to gain traction in global conservation circles, adequate testing of the reliability of these methods remains a high priority if those data are to be used to support PA management decision-making. I use Generalized Linear Models (GLMs) to relate CS animal counts to a variety of environmental and anthropogenic variables. These models are then used to predict species abundance at the sites of our traditional sampling data, and the proportion of reasonable predictions is reported as a measure of CS reliability. Concerns about the suitability of GLMs for CS data analysis are discussed in this chapter.

I conclude in Chapter Four by summarizing my key findings and outlining several important directions for future research on fine-scale animal monitoring in East Africa and CS methods in general. I expand upon the issue of data reliability, describing methods for investigating the effect of observer bias in CS datasets.

Chapter Two | Problems and Prospects for Citizen Science in East African Protected Areas

Best practice recommendations from CS programs in developing countries are still few and far between, and there remain numerous problems associated with the efficacy of CS in non-Western contexts. Several scholars have outlined the potential for CS monitoring methods to succeed in rural African landscapes, citing the falling costs of mobile technology and the rising trend of community-based conservation programs (Chandler et al. 2012; Newman et al. 2012). While these developments are valuable, and represent exciting opportunities in certain contexts, they overlook some of the broader logistical and social factors associated with the implementation of CS programs in East Africa. This paper describes some of the problems and prospects of a CS method for monitoring wildlife in a small conservancy in southwestern Kenya. One important challenge that remains unaddressed for CS in East Africa is whether the governments and political authorities will condone this type of public participation; or better, *why* they will permit to access these protected areas (PAs).

“Safari Science”

At the most basic level, there is the need to first define the “citizen” in citizen science. Tourism is a leading source of foreign exchange in many East African economies (Akama 1997). Tourists have become the group with the most access to PAs, with over 55 million tourist arrivals in Africa last year (UNWTO 2014). The infrastructure is already in place for leveraging tourism as a source of much needed data on wildlife locations and number. However, the establishment of PAs within East Africa has come at the expense of conservation policies that exclude or severely limit the access that local people have to key resource areas (Brockington 2002). Therefore, CS programs that prioritize data over public engagement will likely target tourists rather than local communities for their participants. For this reason, we chose to investigate the feasibility of implementing a CS program within existing safari tourism.

While the term “citizen science” is conventionally used to describe public participation in research, the participants of our program are not the average citizens of East Africa – they are from entirely different countries and economic strata than the local communities that live around PAs. This study coins the term “Safari Science” (SS) to describe this program. More explicit than “citizen science”, this term captures the very specific type of participant that is found in East African tourism. While the potential exists for increasing the participation of local communities within this safari tourism infrastructure – for instance, driver guides, school groups, or lodge employees – it will require significant support at a managerial level.

This paper describes observations of SS during a trial period of 13 weeks from May to August 2013 in a conservation area in southwestern Kenya. It is important to note that the aim of the study was to test the reliability of the data produced by participants in a tourism context, which we address in Chapter Three. Here I focus on the feasibility of incorporating CS programs into East African PAs, emphasizing the logistical barriers to successful monitoring.

Olare Motorogi Conservancy, Kenya

Bordering the Maasai Mara National Reserve, the Olare Motorogi Conservancy (OMC) was established in 2006 by a board of private investors who leased the individual plots of 277 Maasai landowners. It is 136.5 square kilometers of savanna habitat, patrolled on foot and in vehicles by 22 locally trained and recruited rangers. This region contains some of the highest densities of wildlife in Africa (Waithaka 2004), and the annual wildebeest migration in May through October draws large numbers of tourists (Butt 2011). Though there are nine tourist lodges located within or directly adjacent to the OMC (Figure 2), only five of these are considered members of the conservancy and permitted to take guests on game drives within the OMC borders. This makes the conservancy one of the least densely toured protected areas in the region with approximately 750 guests nearly filling bed space in June and July 2013. The size of the conservancy, and the manageable number of participating lodges, made it an ideal study site for our investigation into the reliability of citizen science monitoring methods.

Methods

The aim of this study was to test whether CS methods could produce data of similar quality and quantity as traditional ecological sampling methods. To do this, I designed two independent methods to gather spatial and demographic data for twenty-nine representative species (Table 1). These species were selected from the methods used in the Mara Count of 2002 – the last comprehensive wildlife census conducted in the area (Reid et al. 2003). Both methods gathered data on: wildlife species, time of encounter, GPS location, bearing (using a compass), distance to animal (using a laser rangefinder), and animal count.

For *method 1*, marketed as “Safari Science”, tourists used inexpensive tablet computers (Samsung Galaxy Tab 2 ©) equipped with a mobile application (Memento Database ©) to streamline data entry. For *method 2*: my research team collected data using ecological transects (Figure 2). These transects were chosen in collaboration with OMC management to identify roads that crossed the conservancy and were heavily traveled by tourist game drives. I give a more detailed account of methods in Chapter Three.

Methods for Attracting Participants

The OMC is modeled as an eco-tourism destination, committed to the conservation of endemic wildlife. Given the type of person that would self-select into this environment, I assumed that the majority of lodge guests would be interested in contributing part of their safari time to conservation. In order to recruit tourists as safari scientists, I first approached guests staying at the respective lodges and camps 20 minutes before a scheduled afternoon game drive. I began with a brief, five minute discussion that described the continuing declines in wildlife populations throughout East Africa and the monitoring problems plaguing conservation efforts like those at OMC. This was often enough to catch the attention of tourists who were willing to contribute their time and effort to helping conserve this ecosystem. I was always able to find at least one person per game drive who was willing and interested in using Safari Science.

However, some lodge managers elected to identify guests to participate in the program on their own. One manager chose to present SS as a unique opportunity to each tourist: he would begin by

describing the problems with wildlife conservation and management. Then he would use what he had observed about the guest to personalize the pitch, emphasizing why he thought that person would be particularly *good* at this kind of research, and why they were essential to the success of this research. This approach yielded a higher percentage of willing participants than any other camp.

The lodge managers at other camps admitted their lower recruitment rates were due to a lack of time and personal interest in the subject matter, rather than the nature of the guests themselves. One manager cited fear of poor Trip Advisor reviews, and a personal distaste for data collection, as the major obstacles to aggressively pursuing this project. Another lodge had hired a new manager starting that season, who was busy learning the ropes and unable to devote much time to the project. One manager said we could try to implement the program at his lodge, but he expressed doubts that tourists would be interested in this kind of activity and refused to participate himself in eliciting their participation.

Without support from managers, this study encountered significant logistical barriers. When managers could not be relied upon to deliver the SS pitch to their guests, my research team had to divert considerable time and funds to traveling to each lodge in time to catch tourists before their afternoon game drives, in order to elicit their participation ourselves. From my discussions with OMC staff, these logistical and preferential qualities are common in the area, which could present a significant obstacle to implementing successful, long-term SS programs.

The Training Process

Once a guest agreed to participate, a short ten minute training was conducted that walked guests through the data entry process. This involved learning to use the tablet and application, aiming and reporting rangefinder values accurately, and reading a compass bearing. Some managers felt more comfortable performing this task themselves. They would often work it into the daily routine of the guests, perhaps after meal times, rather than risk overwhelming participants right before they left on a game drive. My research team felt the 10 minute training session was enough time for people to grasp the main functions of the tablet and the correct usage of the compass and rangefinder. I included cards in the tablet cases that reviewed proper use and troubleshooting of the equipment, but we never received a report of anyone referring back to them.

Despite the perceived ease of the data entry process, and the restrictions we built into the data entry forms, I still flagged many entries as improbable or impossible given the constraints of the system and the materials. For example, some entries listed the animals as occurring over 500 meters away from the vehicle, though the rangefinder had a limited range of only 400 meters. These kinds of errors can be controlled for with more heavy restrictions on the data entry forms; this study made all answers mandatory, but did not limit the range of values to only plausible responses. In some cases, it might be preferable to allow improbable answers to be reported, as this can aid the analyst's ability to detect which observers are less reliable than others.

Many citizen science programs have focused on extensive training of volunteers as a method for mitigating observer error or bias in the data generated (Dickson et al. 2010). It is not clear whether data quality improves when volunteers are trained by professionals compared to being self-taught (Dickinson et al. 2010). However, there is a wide range of training styles and lengths in CS programs, and the appropriate style and duration of training will differ with sites and with species. To give two

extreme examples, Mumby et al. (1995) required an intensive 8-day training process for marine life identification and survey techniques, while Ericsson and Wallin (1999) offered no training to the hunters who volunteered to report moose abundances. Both methods reported mixed results regarding data quality, indicating that training duration may not be as significant a predictor of volunteer performance as other measures, such as interest and motivation.

Data Quality and Data Quantity

Of the five member lodges in the OMC, only four were available to participate in Safari Science, and of the estimated 750 guests that stayed in these lodges during our period of data collection (June 4 to August 7), 69 agreed to participate— a 9% response rate. The participants were from a variety of countries and continents, with a majority from Europe and the USA (Figure 3). An additional 13 people participated in the study – one group of middle school students from nearby Endoinyo-Erinka Primary School, and two guides from the lodges who took over when guests refused to continue collecting data. These 82 participants recorded 618 animal sightings over 49 game drives, totaling 1,324,123 animals¹.

Our findings suggest that there is a distinct “carnivore bias” found in the SS data, with predators (lions, hyenas, leopards, cheetahs and jackals) contributing up to 17% of the total sightings, with a heavy emphasis on lions. A likely explanation for this bias is attributable to a longstanding project, “Living with Lions”, which had been working with OMC guides for over a year to encourage them to report lion sightings. This training, combined with guests’ preferences for viewing carnivores over more commonplace animals, probably affected the willingness of the guides to stop at these sightings and allow the guests to enter the data into Safari Science.

These kinds of biases can be reduced by increasing participation rates; a larger number of sightings will dilute a bias that dominates in a smaller dataset (Bonter and Cooper 2012; Dickinson et al. 2010; Hochachka et al. 2012). However, it can be difficult to increase participation without sacrificing overall data quality. This study focused on collecting very specific information at fine scales, which resulted in low levels of participation; many other citizen science programs seek to boost participation by streamlining and simplifying their data collection protocols (Bonney et al. 2009; Marshall et al. 2012).

Unfortunately, simple protocols sacrifice data quality to a significant degree, introducing unknown sources of bias or variability through less rigorous methods – often rendering the data no longer useful for ecological inference (Ericsson and Wallin 1999; Hochachka et al. 2012). This was not acceptable given that the focus of this study was to produce high-quality data, and I emphasized using a more rigorous sampling method (distance sampling). A significant challenge for future SS programs will be to find a balance between the quality of the data – needed for effective management – and the willingness of participants to learn more advanced sampling methods and equipment. From my experience with the guests in the OMC, there are very few tourists willing to devote holiday time to collecting data on the scale of this initial Safari Science program.

¹ One sighting reported 1,000,000 wildebeest, which was flagged as impossible and removed from our analysis.

Managing Expectations

One explanation for the low response rates is that the Safari Science program did not match tourists' expectations of an East African adventure. There were many guests who refused to participate for reasons of holiday relaxation, and because they felt that the experience detracted from game watching time. One couple listened to the SS pitch from a lodge manager, and responded that they were here to "escape the stress of their everyday lives...[including] technology". The mobile application that we designed for improved data entry was seen as something that didn't fit into the guests' expectations of what an African safari experience *should* be. The OMC lodge websites represent broader trends in safari tourism by offering "an African Safari dream", where people can come to commune with "uncrowded wilderness" in "the Africa of the mind's eye" (Olare Mara Kempinski, Kicheche, Mara Plains). This rhetoric and imagery creates an unrealistic image of a primitive landscape untouched by the modern world. Rather than surprise the guests with SS upon their arrival, a research safari option can be built into the vacation packages being sold through lodge websites and travel agents.

Spatial heterogeneity in the sampling effort was also a concern for the SS program, as driver-guides tend to follow specific patterns in their game drives. They rely on past experiences to guide their routes, focusing on specific species of interest to the tourists. This kind of bias could again be mitigated by a planned research safari option, where one of the morning or afternoon game drives is devoted to following an established set of ecological transects laid out by wildlife managers in the area. Integrating the research safari into the tourists' overall adventure would not be farfetched, and could have considerable effect on the potential for successful CS programs in the future.

Scaling Back, Scaling Up

It does not appear that the protocols were the most damaging to participation numbers, as participants varied drastically in the number of sightings they were willing to record, ranging from 1 to 157 entries for a single game drive. This tells me that while some people may have felt the protocols were too cumbersome, many others did not have any problems using the equipment. Indeed, the majority of the participants reported a positive experience with Safari Science, whether or not they recorded many sightings.

Still, some safari scientists reported a desire to improve the efficiency of the mobile application on the tablet – notably the ability to enter multiple species per set of GPS coordinates. One guest left a note for me describing his experience:

“Cara – The system does not allow for multiple species per entry...Our first stop had 17 hartebeest, 3 topi, 6 zebra, wildebeest and Grant's gazelle. After several minutes of trying to enter counts, I give up. I'm sorry but I'm not willing to spend this much time of my safari. Good luck, I hope you get your data.
– George Wagner”

George's feelings were mirrored by many other guests, most of whom refused to participate from the beginning. One of the biggest hurdles to overcome when engaging tourists in CS proved to be convincing them to devote precious holiday time to something new, which could potentially distract them from their enjoyment of wildlife viewing.

This study was done on a Master's budget, and with such limited preparation time, we were unable to program the ideal interface for SS. A sleek, sophisticated and easy to use mobile application would likely attract considerably more interested participants. Additionally, higher-quality tablet computers could be purchased that allow the guests to use an internal compass for bearing readings, which would reduce the need to learn another piece of equipment. The possibility of incorporating photography into the SS collection protocols was mentioned by more than one manager or participant, as that is the main activity on these game drives. While it could be a useful method for validating the accuracy of volunteer counts, I do not feel it should replace the distance sampling protocol as it would compromise data quality too severely.

I also presented tourists with a rather overwhelming list of species – though many participants expressed a desire to record even more species, the data show that a very few species were preferentially reported (see Chapter Three). By scaling back the complexity of the mobile application interface, and limiting the number of species to those of higher interest to volunteers, the SS program could scale up to a much larger participant base fairly easily without sacrificing the quality of the collection process. Whether or not the species that most interest volunteers would also be the species of highest ecological importance remains to be seen.

Reward Systems

These findings indicate that reducing the complexity of the data collection protocols might not be necessary if the participants are given sufficient incentives and rewards for their time and effort. Lodge managers and volunteers alike strongly emphasized the need for participant reward systems. These recommendations ran from the simple - like free drinks, or symbolic badges of achievement - to the more computationally complex. Carine Hals, Safari Science participant and student in Geographic Information Technology, sketched out her ideal interface for future versions of the mobile application, including her vision for the guests' end product. The result was a map showing the path of the game drive, points for locations of animal sightings, and a list of species and counts on the side. All of this would be emailed to the participant at the end of game drive when they returned to wireless internet access at the lodges. Another participant expressed an interest in uploading their findings to a common website, where they could compare their sightings with other guests'. This, the man said, was what they did in the lodge common areas already.

Future Considerations

My experience at OMC demonstrates that while there are many opportunities for SS in the tourism communities of East Africa, there are equally compelling challenges that must be addressed in order to establish successful and sustainable programs. Citizen science is a complicated monitoring method to implement correctly, as it is both logistically and computationally challenging to produce data of useful quality for management. These findings point to two cornerstone issues that will determine the success of such a venture: ownership over the program, and use of the data produced by it.

Program ownership must come from a well-established and fully supportive management team; the implementation and continuation of a SS monitoring program requires full-time staff devoted to maintenance and troubleshooting along the way. This study finds that if SS is to provide data that can be meaningfully absorbed into everyday conservation management practices, then it cannot occur as an ad-hoc enterprise. Based on my experience with the guests and lodge managers at the

OMC, it seems unlikely that small conservancies have the available human and financial resources to devote to a full-scale, independent SS project, though this does appear to depend in large part on the individual managers involved. Large tourist lodges, with hundreds of guests per night, are more common in larger PAs like the National Parks and Reserves. Centralizing SS programs in larger lodges would eliminate much of the logistical difficulty I encountered at OMC, and the higher numbers of guests would likely result in larger, more useful data sets.

The second main obstacle towards a scalable Safari Science program involves the demand for and analysis of the data produced. SS data must be proven useful to PA managers if they are expected to contribute already strained resources towards program development and maintenance. Unfortunately, the level of statistical skill required to manipulate SS data and interpret the results is outside the experience of most PA managers. It is furthermore unlikely that individual PAs will be able to fund the external analysis of their SS data without increased state support. Partnerships with local and international researchers could also be leveraged to provide a rotating source of manpower for the analysis and interpretation of large SS data sets. A number of development agencies, non-governmental organizations, and academic institutions are already actively engaged in wildlife conservation initiatives throughout East Africa. If the logistical challenges of SS programs can be met and overcome on the ground, these institutions present a likely source of technical and financial backing for future, region-wide ventures.

Chapter Three | Safari Science: Testing Tourists as Researchers in East African Protected Areas

As citizen science (CS) methods continue to gain traction in global conservation circles, adequate testing of the reliability of these methods remains a high priority (Crall 2010; Danielsen 2005). Many CS programs design data collection protocols that facilitate ease of volunteer involvement, resulting in sampling biases that complicate analysis and could result in misleading ecological inferences (Hochachka et al. 2012; Tonachella et al. 2012). However, few studies to date have focused on this important issue by directly measuring the quality of CS data with regards to more conventional ecological sampling techniques (Bernard et al. 2013; Darwall and Dulvy 2003; Delaney et al. 2008; Ericsson and Wallin 1999; Foster-Smith and Evans 2003; Genet and Sargent 2003; Moyer-Horner et al. 2012; Mumby 1995; Nagy et al. 2012; Penrose and Call 1995; Vianna et al. 2014). This study is the first to test the reliability of tourists as citizen scientists in the context of East African Protected Areas (PAs).

Conclusions on the overall reliability of CS data are still hampered by a lack of evidence and contradictory findings. For example, Bernard et al. (2013) found that CS data was of lower quality than scientists' when looking at the community-level estimates. However, this trend did not hold when the data was broken down into abundant and rare species – volunteers and scientists performed virtually the same when estimating common species. Dickinson et al. (2010) report an opposite finding, where volunteers are more likely to over-report rare species and under-report common species. Delaney et al. (2008) report age as a significant predictor of observer skill, but Newman et al. (2003) did not find it to be. Ericsson and Wallin (1999) maintain that hunter observations of moose reflect the overall population size and fluctuations rather well, but these data could not directly replace more expensive, conventional sampling methods unless they first undergo some calibration process. Most studies agree that observer error varies widely depending on the species and the system being studied (Dickinson et al. 2010), which reinforces the need for more quantitative, site-specific studies of CS data.

The primary objective of this paper is to test whether CS methods can produce data of similar quality and quantity as traditional ecological sampling methods in an East African savanna context. To do this, I designed two independent methods to gather spatial and demographic data for twenty-nine representative species (Table 1). These species were influenced by those used in the Mara Count of 2002 –the last comprehensive wildlife census conducted in the area (Reid et al. 2003) – and previous studies on wildlife distribution in the area (Bhola et al. 2012a). I identified species that were active during the daytime, relatively common, and easy for tourists to identify while still representing the range of animal guilds present in the system.

In method 1, “Safari Science” (SS), tourists used tablet computers to collect data while on game drives. The use of mobile technology to streamline data entry and correct for errors is relatively new to the field. In method 2, “Traditional Sampling” (TS) my research team collected data using the common ecological method of line transects. I fitted generalized linear models (GLMs) to the SS data, and validated those models by predicting to the TS data observation locations. I use this

validation process as an assessment of citizen science data reliability. This paper reports on the findings of our study trial period of 13 weeks from May to August 2013 in a private conservancy in southwestern Kenya.

Modeling the Species-Environment Relationship

PA management can be aided by the development of predictive models that capture the relationship of species and their habitats (Guisan and Zimmermann 2000). Ordinary least squares (OLS) and its generalized form (GLS) are often used for modeling species-environment relationships (Guisan and Zimmerman 2000; McCullagh and Nelder 1989). OLS assumptions of independence and constant variance are often violated when sampling landscape variables, and thus GLS is often preferred to OLS (Tonachella et al. 2012).

As the field evolves, novel methods have been proposed to predict species abundance, turning to machine learning and data mining techniques (i.e. multivariate adaptive regression splines, classification and regression trees, genetic algorithms, and maximum entropy models) (Elith and Leathwick 2009). These are often “black box”, statistically complex methods and software that require significant learning curves (Elith et al. 2006). There is also growing toolbox of sophisticated spatial analysis methods that can help account for autocorrelation or observer effects in species-environment models (i.e. autoregressive models, geostatistical methods, Generalized Estimating Equations, and Generalized Weighted Regression) (Dickinson et al. 2010; Elith and Leathwick 2009).

While I recognize that there are perhaps more appropriate analytical techniques for Safari Science data, notably hierarchical mixed models and specifically generalized linear mixed models (Latimer et al. 2006; Tonachella et al. 2012), I decided to use an analytical technique that is familiar to most trained ecologists. Generalized linear models (GLMs) are a well-accepted method for estimating species-environment relationships, as they have a strong statistical foundation and can fit a realistic, nonlinear relationship with the response (Austin 2002; Elith et al. 2006; Elith and Leathwick 2009). As a secondary objective of this paper, I examine the suitability of GLMs for the analysis of CS data. I discuss common issues encountered, such as variable selection, overdispersion in count data, and model evaluation. As GLMs are the preferred method for most ecological analyses, I intend to assess whether GLMs can be used with CS data to report accurate estimates of wildlife abundance.

Methods

Study Site: Olare Motorogi Conservancy

Bordering the Maasai Mara National Reserve, the Olare Motorogi Conservancy (OMC) was established in 2006 by a board of private investors who leased the individual plots of 277 Maasai landowners. It is 136.5 square kilometers of savanna habitat, in a region that contains some of the highest densities of wildlife in Africa (Waithaka 2004). The vegetation is primarily open grass plains, with occasional patches of *Acacia gerrardii* and *Terminalia* trees, shrublands and riverine woodlands (Bhola et al. 2012a). Rainfall is bimodal, with the short rains falling in late November-December, and the long rains during March-June. The annual wildebeest migration from May through October draws large numbers of tourists (Butt 2011). Though there are nine tourist lodges located within or directly adjacent to the OMC (Figure 4), only five of these are considered members of the conservancy and permitted to take guests on game drives within the OMC borders. This makes the

conservancy one of the least densely touristed PAs in the region, with approximately 750 guests nearly filling bed space in June and July 2013. The size of the conservancy, and the manageable number of participating lodges, made it an ideal study site for my investigation into the reliability of citizen science monitoring methods.

Fieldwork

Both methods performed distance sampling using ground-vehicle line transect surveys (measured out to 200m from the road), which are subject to sampling biases such as a lack of measured sampling effort, restriction to roadsides, and overestimation of group sizes (Ogutu et al. 2006). Distance sampling is one of the most widely used methods for estimating animal populations, though it can be a rather difficult methodology for amateurs due to the need for accurate distance measurements and a tendency for “imperfect detectability” of species (Buckland et al. 2004; Marquez 2009; Tonachella et al. 2012).

These methods also represent a form of “convenience sampling” in that all sampling is done via permanent or seasonal paths through the study site, and as such is biased to animals located along roadways (Anderson 2001). However, the objective is to test the reliability of one method vis-à-vis another, and tourist game drives prefer to stay near well-established roadways rather than risk guest discomfort and vehicle quality on rough off-road excursions. Therefore, I will restrict the analysis to this comparison with the understanding that the methods have this inherent ecological bias.

Despite these concerns, distance sampling using vehicle-based line transects are a common and cost-effective method for monitoring wildlife (Ogutu et al. 2006; Singh and Miller-Gulland 2011). Both methods gathered data on: wildlife species, time of encounter, GPS location, bearing (using a compass), distance to animal (using a laser rangefinder), and animal count. The methods were temporally consistent, with morning (6:00-9:00) and afternoon (15:00-18:00) sampling sessions. Observations were restricted to the OMC to maximize the spatial consistency across methods, as tourists and researchers were unable to follow the same roads/transects at the exact same times.

Traditional Sampling Method

Four transects were chosen in collaboration with OMC management to identify roads that covered the largest extent of the OMC while remaining heavily traveled by tourists (Figure 4). These transects were approximately 11.5km each in length. Observations followed this pattern: (i) upon sighting an animal, the vehicle stopped and a GPS location was taken, (ii) distance to the animal was measured with a Simmons laser rangefinder, (iii) direction to the animal from the observer location in the vehicle was taken with a Suunto compass, (iv) animals were counted. Each transect was run once a week (twice a day) for a total of 4,800 animal sightings across 42 data gathering sessions.

Safari Science method

Tourists were recruited from four of the five member lodges in the OMC. I relied on managers to inform guests of the study, assess their interest in participating, and deliver the ten-minute training I had devised. Halfway through the data collection period it became apparent that a more hands-on recruitment method was required, as managers were either uninterested or over-worked and unable to contribute significant time to the project. I then met tourists in the 20 minutes before they left for

a game drive, and explained the process of using the tablet, Simmons rangefinder, Suunto compass, and estimating animal counts. Tourists used inexpensive tablet computers (Samsung Galaxy Tab 2 ©) equipped with a mobile application (Memento Database ©) to streamline data entry. Game drives do not follow set roads, as guides rely on scouts to report current animal locations. A total of 82 participants recorded 618 animal sightings across 49 game drives. Only 348 of these observations occurred within our study site.

Data Analysis

I use a GLM framework to relate animal abundance to the set of six environmental variables. I fitted species-specific models to the SS data, using stepwise elimination of our variables to find the simplest expression that best described the variability. I then validated these models by predicting animal abundance at the independent, TS sampling points. I calculated the number of TS observations that fell within the 95% confidence interval of the SS model predictions, and used this as an estimate of the accuracy of CS data. All data analysis was performed in R 3.0.2 (R Development Core Team 2012).

Due to issues with volunteer motivation and interest, the SS data were limited for many species. I selected the nine most abundantly reported species for our analysis. Lions, wildebeest, topi, impala, elephants, buffalo, zebra, Grant's gazelle, and giraffes were selected for this analysis based on the number of observations available from both methodologies.

Variable Selection

It is common practice to predict species distributions on the basis of ecological parameters, as species are expected to be non-randomly distributed in relation to eco-geographical variables (Guisan and Zimmermann 2000; Hirzel et al 2002). Models that evaluate the species-environment relationship use independent environmental variables including topographical features (slope, altitude), ecological data (vegetation cover, density), and human superstructures (distance to town, road density) (Hirzel et al 2002; Paudel et al. 2012).

Austin (2002) categorizes three “resource gradients” that variables will align with, and notes that indirect resource gradients – variables like elevation, that do not have direct physiological effects on the species of interest – should be discarded in favor of more direct resource gradients that have higher ecological significance. Indeed, stepwise variable selection in species-environment modeling is criticized by many researchers, who recommend careful thought and planning go into selecting and using only variables with high ecological significance (Elith and Leathwick 2009). Numerous studies have examined the relationship of wildlife distribution to landscape and anthropogenic factors in the Mara region, most recently Bhola et al. 2012, Odadi et al. 2011, and Ogutu et al. 2011. With these studies in mind, and my experiences in the field, I identified six environmental variables that have high potential for predicting the habitat preferences of the species of interest.

Given the sampling bias of the surveys, which took place along the roads of the conservancy, distance to road was not used as a variable. Animal distributions in the East African savanna are primarily mediated by vegetation productivity (Odadi et al. 2011), and many of the variables chosen for this study reflect that important relationship. Grass height is an indicator of both forage quality and predation risk (Bhola et al. 2012a), which I discuss more thoroughly for each variable below.

The Normalized Difference Vegetation Index (NDVI) is a remote sensing product that represents the productivity and biomass of vegetation in an area (Pettoirelli et al. 2005). Higher NDVI corresponds to taller, more mature grasses and trees, which are often used by predators for daytime shelter (Ogutu et al. 2006). NDVI has been used successfully to predict the distribution and abundance of large herbivores (Pettoirelli et al. 2011). As small to medium sized animals have a high risk of predation in tall grasses or dense vegetation, I expect a negative relationship with NDVI (Bhola et al. 2012b). I expect a positive relationship with NDVI for larger animals, like elephants and buffalo, as they require considerable quantities of food and do not have as large a risk of predation (Bhola et al. 2012a; Sinclair et al. 2003).

Geomorphological traits of the landscape – like slope or elevation – could be impacting the distribution of wildlife in the Mara region (Bhola et al. 2012a; Ogutu and Dublin 2004). Slope is related to soil depth and texture, and can thus be considered a measure of potential soil moisture (Franklin 1998). Slope often represents difficult or rocky terrain, which some species may avoid for lack of quality vegetation and others might prefer for the ability to detect and evade predators. Based on observations during fieldwork, I expect the small, mixed feeders - impala and Grant's gazelle - to have a positive relationship with slope. I expect the mid to large sized species will have a negative relationship, as they tend to prefer flat plains.

Distance to rivers is an indicator of dense or abundant vegetation, as riverine woodlands occur alongside permanent and semi-permanent water bodies. Distance to river also represents an increased risk of predation, as riverine woodlands are ideal habitats for predators during the daytime (Ogutu et al. 2006). Similar to NDVI, I expect smaller species to avoid rivers and the threat of predation, while larger species should not be as affected by this condition.

Topographic wetness index (TWI) is a measure of long-term soil moisture availability (Iverson et al. 1997; Wilson and Gallant 2000). Areas with high TWI are more likely to have tall vegetation, and thus high food quantity. As with NDVI and riverine vegetation, this could perhaps represent increased predation risk. In this analysis, we also use TWI as a proxy for temporary or seasonal water bodies, as this study occurred in the late wet season and many species are known to congregate near such water sources (Owen-Smith 1996; Western 1975). Other studies have found herbivores avoiding the wet and sticky soils in low-lying areas (Talbot and Talbot 1963), which could indicate a quadratic relationship as species prefer a certain level of soil moisture.

Finally, the distance to lodges and park boundary variables are indications of the sensitivity of the species to anthropogenic influences. The OMC is bordered on three sides by sporadic human settlements, so we expect some species will avoid these places and the associated conflict with humans and dogs (Lamprey and Reid 2004; Ogutu et al. 2011). However, livestock grazing keeps grasses on the OMC edges in a short, active growth stage, which increases the food quality and also the visibility against predators, creating a safe grazing site for smaller species (Bhola et al. 2012a; Ogutu et al. 2005). The lodges in the OMC are generally small and low-impact, so I do not expect a strong avoidance of them. It should be noted that the lodges in the OMC are located along the main waterway, the Ntiakatiak River, which could inflate the number of predators seen near lodges.

I examined these variables for multicollinearity, and found the strongest Pearson's correlation (0.5) between the distance to lodge and distance to river variables (Table 2). While this could just be a reflection of the proximity of the lodges to the Ntiakatiak River, it could also be an indication of

sampling bias, with most points occurring close to the lodges and rivers. I did not consider it a strong enough correlation to warrant removing either of the variables.

Data Collection and Processing

Ecological factors can be difficult or expensive to measure in the field, but remote sensing products and GIS technology allow us to approximate them with relatively high accuracy. Digital elevation models (DEM) tend to be fairly accurate, and thus topographic variables can be generated without much loss of precision (Guisan and Zimmerman 2000). I relied on a 2011 30-meter DEM from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and imported it into ArcGIS (ESRI 2010) to generate the slope and elevation variables used in the analysis. These layers were then used in the creation of a topographic wetness index (TWI), or potential for saturation at the soil surface, which is related to the potential for higher plant productivity (Wilson and Gallant 2000). This variable was created using the formula

$$TWI = \ln(AS/s)$$

where AS is the catchment area and s is the slope.

The MOD13Q products - Normalized Difference Vegetation Index (NDVI) data - at 250m resolution were downloaded from the Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC) for the fieldwork season. I then averaged four products in ArcGIS to create one aggregate NDVI layer for the entire season. A 1:50,000 scale topographic sheet from the Survey of Kenya was digitized by the International Livestock research Institute to create a shapefile of the major rivers and streams. We performed Euclidean distance calculations in ArcGIS to generate the ‘distance to water’, ‘distance to lodges’, and ‘distance to boundary’ variables. The GPS points of animal locations were imported into ArcGIS and the data from the environmental variable layers (NDVI, slope, elevation, TWI, distance to water, distance to lodges, and distance to boundary) were extracted to each point.

Model Formulation

Count data, Y_i , for one particular wildlife species at one point i follows a quasi-Poisson distribution with mean λ_i and equal variance, multiplied by a dispersion factor σ

$$Y_i \sim \text{quasi-Poisson}(\lambda_i, \lambda_i * \sigma)$$

The process models use a log link, which we can write as

$$\log \lambda_i = \alpha + X_i * \beta_i + X_i^2 * \beta_i$$

where α is the intercept, X_i represents the continuous, environmental variables in both linear and quadratic form, and β_i are the estimated regression coefficients.

In keeping with the quasi-Poisson distribution, I performed model selection for each species using the *drop1* method outlined by Faraway (2006) and by Zuur et al. (2009), where the F statistic is calculated for each variable instead of the more common Chi-squared analysis of deviance. Variables with high residual deviance were removed in a stepwise fashion until the minimal adequate model remained (Crawley 2013). The minimal adequate model generally contains only significant variables, but often a statistically insignificant variable with low residual deviance and potentially high

ecological significance was left in. Due to potential impacts from edge effect, competition and predation, which could result in nonlinear environmental relationships, I included the quadratic terms of all variables in the original maximal model (Crawley 2013; Nagy et al. 2012).

Overdispersion

Count data in ecology are often overdispersed - where the variance of the counts is larger than the mean (Ver Hoef and Boveng 2007; Zuur et al. 2009). Hilbe and Greene (2007) describe potential causes for “apparent overdispersion”, such as missing covariates or interactions, outliers in the response variable, non-linear effects of covariates that are represented as such in the model, and the choice of the wrong link function. When none of these causes exist in the data, we can assume the overdispersion is then real and inherent in our data, rather than a model misspecification. In that case, ignoring it could result in very different biological conclusions (Zuur et al. 2009). Though most overdispersion is seen as a result of some missing explanatory variable, it is also possible that geographic factors are influencing the animal locations (fire, disease, dispersal mechanisms or other biological factors) (Elith and Leathwick 2009). I could not identify any other environmental parameters to add to the model, and I also did not find significant outliers in my exploration of the data, so I am left with the assumption that some geographic influence is at work on these data.

To find the level of overdispersion in the data, I fit a standard Poisson GLM to the data and used the *dispersiontest* function in the R package “AER” to estimate a dispersion factor (σ). I found evidence of overdispersion for all species in the analysis, and proceeded to use a quasi-Poisson regression model to correct the standard errors (Wedderburn 1974; Zuur et al. 2009). The quasi-Poisson GLM assumes the variance is equal to the mean, multiplied by some dispersion factor (σ). This treatment is generally quite robust, though there is an observed decline in the significance of the predictor variables, as each standard error is multiplied by the square root of the dispersion factor (Heinzel and Mittlbock 2003; McCullough and Nelder 1989; Zuur et al. 2009).

Model Evaluation

The accuracy of the GLMs I use in this analysis is an important part of this paper’s objective, as large errors or incorrectly designed models may result in misleading conclusions regarding the accuracy of CS methods. When creating GLMs for prediction versus extrapolation or ecological inference, there must be some balance between model fit with the training data and the generality that allows the model to predict well to unobserved locations (Elith and Leathwick 2009). As the primary objective is to test the reliability of SS data in making predictions of species abundance in unobserved locations, I emphasized the importance of the predictive performance of each model.

During our model simplification, I periodically validated its predictive performance on the independent TS dataset. If a model was not making reasonable abundance predictions in the validation dataset, it was simplified further until those predictions became plausible. The final predictions, and their corresponding uncertainties, were used to measure the overall accuracy of SS data for that species. It is important to remember that the quasi-Poisson GLM is fit by quasi-likelihood; it does not necessarily have a distributional form and therefore one cannot use the standard coefficient of deviation (R^2) or AIC statistics for model evaluation (Ver Hoeff and Boveng 2007). Therefore, the fit of the model was assessed by examining patterns in the deviance residuals, which is the default in R and in most cases does not differ significantly from the standardized Pearson’s residuals (Faraway 2006; Zuur et al. 2009). I plotted the deviance residuals against (i) fitted values, (ii) the explanatory variables, (iii) time, and (iv) spatial coordinates.

Results

Volunteer Preferences and Motivation

The willingness of tourists to participate in a Safari Science program was low, demonstrated by an average of only 12.6 sightings per game drive (compare to 114 sightings per TS sampling session). Broken down by species, volunteers were most likely to report lions, wildebeest, topi, impala, elephants, buffalo, zebra, Grant's gazelle, and giraffe. The most commonly reported species in the TS dataset were: Thomson's gazelle, wildebeest, topi, impala, zebra, Grant's gazelle, warthog, domestic cattle, and domestic sheep or goats. Volunteers reported very few Thomson's gazelle (14 observations), which are the most common species in the region. Even when both methods reported the same species, the number of observations differed by hundreds to thousands of records (Table 3). Only elephants and buffalo were reported in similar numbers across both methods.

Model Results

The best models for each species are reported in Table 4. The values of the regression coefficients and their standard errors are reported in Tables 5-13. Figures 5-22 show the predicted values (with confidence intervals) and the corresponding observed TS abundances, accompanied by spatial plots of predictions and observations for visual comparison of abundance patterns. Finally, Table 14 gives the number of TS observations that fell within the 95% confidence interval of the predictions, reporting overall accuracy for each species as a percent.

1. Lions

There are 41 lion observations in the SS dataset, and 11 in the TS validation dataset. This is the only instance where SS observations exceeded TS observations. The minimal adequate SS model has two linear predictors: distance to river and TWI (Table 4). Neither is significant, and both show a negative relationship with the response (Table 5). The model explains 5.8% of the deviance in the residuals, and the plot of the residuals versus fitted values has no dominant patterns. Predictions had a reasonable range of error (Figure 5), and the spatial patterns of the predictions matched those of the observed lions reasonably well (Figure 6), though the limited sample size does restrict interpretation. In the model validation, 8 of the 11 TS observations fell within the 95% confidence interval, for an overall accuracy of 72.7% (Table 14).

2. Wildebeest

There are 34 SS wildebeest observations, and 896 TS wildebeest observations. The minimal adequate SS model has three linear predictors: slope, distance to boundary, and TWI (Table 4). Slope and TWI have a negative relationship with wildebeest abundance, though only slope is significant. Distance to boundary is also significant, and has a positive relationship with the response (Table 6). The model explains 43.3% of the deviance in the residuals, but the plot of the residuals versus fitted values has a V-shape, indicating some violation of independence is occurring. Predictions at low values had reasonable errors, but larger predictions had similarly high associated errors (Figure 7), which inflates the number of TS observations that fall within it. The spatial patterns of the predictions did not match those of the observations well: observations show larger wildebeest numbers bordering the Maasai Mara National Reserve (MMNR) to the south, while predictions put the highest wildebeest abundances in the center of the OMC (Figure 8). In the model validation,

775 of the 896 TS observations fell within the 95% confidence interval, for an overall accuracy of 86.5% (Table 14).

3. Topi

There are 31 SS topi observations, and 701 TS topi observations. The minimal adequate SS model has two linear predictors: distance to river and TWI (Table 4). They are both significant, and exhibit positive relationships with the response (Table 7). The model explains 54.4% of the deviance in the residuals, which was the highest proportion explained amongst all the species. The plot of the residuals versus fitted values shows a slight positive quadratic form, indicating some violation of independence is occurring. This is shown in the plot of predicted values, as larger predictions have larger errors (Figure 9). Spatially, the predictions did fairly well, though the TS data show higher abundances in the center of the OMC that are not represented in the predictions (Figure 10). In the model validation, 423 of the 701 TS observations fell within the 95% confidence interval, for an overall accuracy of 60.3% - the lowest of all the species (Table 14).

4. Impala

There are 27 SS impala observations, and 610 TS impala observations. The minimal adequate SS model has three linear predictors: slope, distance to lodge, and TWI (Table 4). Slope is not significant, and shows a negative relationship to impala abundance. Distance to lodge is marginally significant ($p < 0.1$), and has a positive relationship with the response. TWI is significant, and has a positive relationship with the response (Table 8). The model explains 36% of the deviance in the residuals. The plot of the residuals versus fitted values shows a slight positive quadratic form, indicating some violation of independence is occurring. Indeed, the prediction errors are rather large (Figure 11). However, the model predicts the spatial patterns of impala abundance very well when compared to the observed values (Figure 12). In the model validation, 381 of the 610 TS observations fell within the 95% confidence interval, for an overall accuracy of 62.5% (Table 14).

5. Elephants

There are 27 SS elephant observations, and 33 TS elephant observations. The minimal adequate SS model has two linear predictors and one quadratic term: NDVI, $NDVI^2$, and distance to boundary (Table 4). NDVI is significant, and has a positive relationship with elephant abundance. The quadratic term for NDVI is also significant and negative, indicating elephant abundance is maximized at a middle range of NDVI values. Distance to boundary is marginally significant and shows a negative relationship with the response (Table 9). The model explains 39.3% of the deviance in the residuals. The plot of the residuals versus fitted values shows no patterns. Predictions have narrow error bounds (Figure 13), and spatially the predictions match observed elephant abundances reasonably well (Figure 14). In the model validation, 21 of the 33 TS observations fell within the 95% confidence interval, for an overall accuracy of 63.6% (Table 14).

6. Buffalo

There are 25 SS buffalo observations, and 26 TS buffalo observations. The minimal adequate SS model has three linear predictors and one quadratic term: NDVI, distance to river, TWI, and TWI^2 (Table 4). NDVI and distance to river are not significant, and show negative relationships with buffalo abundance. TWI and its quadratic term are both significant. TWI has a positive relationship with buffalo abundance, and TWI^2 has a negative one – again indicating that there is an optimal medium TWI range where buffalo tend to aggregate (Table 10). The model explains 29.8% of the

deviance in the residuals. The plot of the residuals versus fitted values shows a negative trend, indicating some violation of independence is occurring. Predictions have reasonable errors (Figure 15), but the spatial patterns of the predictions do not match the observations well (Figure 16). Observations place the largest buffalo abundances in the center of the OMC, but the predictions show them bordering the MMNR to the south. In the model validation, 43 of the 56 TS observations fell within the 95% confidence interval, for an overall accuracy of 76.8% (Table 14).

7. Zebra

There are 21 SS zebra observations, and 374 TS zebra observations. The minimal adequate SS model has three linear predictors: distance to lodge, distance to boundary, and TWI (Table 4). Distance to lodge is marginally significant, and has a negative relationship with zebra abundance. Distance to boundary is also marginally significant, but has a positive relationship. TWI is not significant, and has a negative relationship with the response (Table 11). The model explains 29.2% of the deviance in the residuals, and the plot of residuals versus fitted values shows a negative trend, indicating some violation of independence is occurring. The predictions have large associated errors (Figure 17). The spatial patterns of the predictions show a clustering similar to the observed values, but concentrated in the center of the OMC instead of along the borders as was observed (Figure 18). In the model validation, 231 of the 374 TS observations fell within the 95% confidence interval, for an overall accuracy of 61.8% (Table 14).

8. Grant's gazelle

There are 18 SS Grant's gazelle observations, and 244 TS Grant's gazelle observations. The minimal adequate model has one linear predictor: slope (Table 4). Slope is significant, and shows a positive relationship with gazelle abundance (Table 12). The model explains 32.1% of the deviance in the residuals. The residuals versus fitted values had slight patterning, though it is possibly due to a lack of data points. The predictions had very narrow errors (Figure 19), and the spatial patterns of the predictions matched the observation patterns reasonably well (Figure 20). In the model validation, 68 of the 244 TS observations fell within the 95% confidence interval, for an overall accuracy of 27.9% (Table 14).

9. Giraffe

There are 17 SS giraffe observations, and 54 TS giraffe observations. The minimal adequate SS model has three linear predictors: distance to lodge, distance to river, and TWI (Table 4). Only distance to lodge is significant, and it shows a positive relationship with giraffe abundance. Distance to river and TWI are not significant, and have negative relationships with the response (Table 13). The model explains 30.8% of the deviance in the residuals. The plot of the residuals versus fitted values showed no dominant trends or patterns. The predictions had very reasonable errors (Figure 21), and the spatial patterns of the predictions matched the observations fairly well, though there was perhaps some overestimation in the center of the OMC (Figure 22). In the model validation, 37 of the 54 TS observations fell within the 95% confidence interval, for an overall accuracy of 68.5% (Table 14).

Discussion

This study tested whether CS data could produce reliable estimates of species abundance, with similar quantity and quality as more conventional ecological sampling techniques. A secondary aim of this study was to assess whether GLMs were a suitable method for analyzing CS data. Due to issues with volunteer motivation and interest, I did not find a similar quantity of data across both methods, with significantly fewer SS observations than TS. In general, this study suffers from these low sample sizes.

Still, I found SS data did fairly well at estimating species abundance, with the accuracy for eight out of nine species ranging between 60 – 87%. However, large errors in the predictions of many species reduce confidence in this measure of performance, as they inflate the accuracy of SS data. I discuss these results per individual species, in separate sections addressing the validity of the ecological relationships described and the evaluation of model performance.

Ecological Inference

Wildlife distributions have been studied extensively in and around the MMNR, and we use the relationships described in these studies as a way to assess the quality of SS data. We compare the sign of the regression coefficients in our SS models to those of other studies, notably Bhola et al. (2012b). Our results are mixed both across and within species, and as with other studies it is difficult to distinguish between error propagated by the model (due to small sample sizes) or error arising from observer bias (Elith and Leathwick 2009; Dickinson et al. 2010). Lion, elephant, and buffalo data show the highest ecological validity of all species.

1. Lions

Research on lion distributions in relation to prey and habitat find that areas of variable topography, more water sources, and patches of shrub or dense vegetation are good indicators of ideal lion territory (Ogutu and Dublin 2004). Riverine woodlands are also known to harbor predators (Ogutu et al. 2006). Therefore the SS model shows sound ecological inference as distance to river and TWI are the environmental variables that explain the most variability in the lion data, with negative relationships indicating lion abundance is highest near these areas.

2. Wildebeest

I find mixed results regarding the ecological validity of SS wildebeest data. Wildebeest show negative relationships with TWI, which is reasonable given my assumptions of increased predation risk and difficult to traverse, waterlogged soils. Slope has a negative relationship with wildebeest abundance, indicating this species prefers lower slopes. Again, this meets my expectations. Wildebeest show a positive relationship with the distance to boundary variable, which contradicts our expectations. Indeed, my observations of wildebeest indicate the species prefers the large, heavily grazed plains on the borders of the OMC (Figure 8).

3. Topi

I find mixed results for the ecological significance of SS topi data. Topi show a positive relationship with distance to river, which is reasonable given my assumptions of increased predation risk in

riverine woodlands. However, topi also show a positive relationship with TWI. This contradicts my expectations (see wildebeest, above), and contradicts the negative TWI relationships described by the wildebeest and zebra models. These species share similar body sizes and grazing preferences (Bhola et al. 2012b), so I would expect a similar relationship to TWI across them. It is possible that topi are being pushed into less favorable grazing areas through effects of competition, though this does not match the many observations of topi and wildebeest in shared herds.

4. Impala

I find mixed results for the ecological significance of SS impala data. The positive relationship with TWI is not as concerning as for topi (above), as the smaller body size of impala increases their ability to navigate heavy, waterlogged soils. The increased predation risk in areas of high TWI would also not affect impala as strongly as larger herbivores, as they are considerably quicker. Therefore, this relationship is ecologically sound. The unexpected negative relationship with slope does not match my expectations, as observations in the field found a high tendency for impala in areas of high slope. Finally, impala show a positive relationship with distance to lodge, demonstrating skittishness with respect to tourism activity.

5. Elephants

I am fairly confident in the ecological validity of SS elephant data. Elephants are less prone to predation due to their large body sizes, and their digestive physiology allows them to eat taller, more fibrous grasses than smaller species (Bhola et al. 2012a), so I expected them to prefer areas of high NDVI. As areas on the edge of the OMC are more heavily grazed by cattle and other herbivores, the tallest grasses are found in the center of the PA. The elephant model matched these expectations with a strong positive relationship to NDVI. The negative relationship with distance to border does not match my expectations, but the wide ranges and large distances traveled daily by elephants could be influencing that variable in a way that I did not anticipate.

6. Buffalo

I am fairly confident regarding the ecological reliability of SS buffalo data. Buffalo show the expected trend with TWI and TWI^2 , preferring an optimal level of soil wetness. Buffalo prefer riverine habitats and high soil moisture (Prins 1996; Ryan et al. 2006; Sinclair 1977), the demonstrated relationships with TWI and distance to river in our model reflect these observed preferences. Somewhat confusing is the negative relationship with NDVI, as I hypothesized they would prefer the taller, dense grasses in the middle of the OMC. However, the relationship was not significant, and Ryan et al. (2006) also found NDVI was not a good predictor of buffalo distributions.

7. Zebra

I find mixed results regarding the ecological validity of SS zebra data. Zebra show a negative relationship with TWI, matching my expectations (see wildebeest, above). Previous work has shown wildebeest and zebra do not differ significantly in grass height preferences (Arsenault and Owen-Smith 2011), and thus my expectation that these species would have similar grazing preferences is upheld. However, zebra also showed a negative relationship with distance to boundary, contradicting my expectations and observations of the species. The negative relationship with distance to lodge indicates zebra are not negatively impacted by tourism activities.

8. Grant's gazelle

I suspect the few data points available for Grant's gazelle prevent strong conclusions regarding the environmental relationships of the species. Slope was the only predictor of Grant's gazelle, explaining a considerable portion of the variability in the data. This supports my expectations regarding gazelle habitat preferences. I expected stronger relationships with variables representing grass height (NDVI, TWI) and increased predation risk.

9. Giraffe

I do not have confidence that SS giraffe data can provide sound ecological inference, though these results are limited by small sample sizes. Giraffe show a preference for habitat farther from the tourism lodges. The model shows negative relationships with the explanatory variables of ecological significance (distance to river and TWI), which is contradictory to my expectations. Riverine woodlands and dense vegetation are more likely to occur close to rivers and in areas of high soil moisture, so I would expect giraffe to prefer these areas rather than avoid them, as giraffe tend to browse trees and shrubs (Caister et al. 2003).

Model Performance

Given the limited sample size, patterns in residual deviance, and the general lack of explanatory power, I find GLMs a difficult and unreliable method for gleaned useful data from SS methods. The process of matching appropriate analysis methods to data is a continuing area of research, and other authors have noted how different approaches to the same dataset can yield contradictory results and conclusions (Dickinson et al. 2010). Tonachella et al. (2012) support this finding regarding the suitability of GLMs for CS data, and recommend incorporating measures of observer bias if these data are to be used for management decision-making.

1. Lions

It is unsurprising that the lion model has a low proportion of deviance explained, as carnivores in general do not have highly specific habitat requirements, making it difficult to predict their abundance based on environmental parameters (Woodroffe and Ginsberg 1998). The model performed very well in the validation process. I did not find any patterns in the plots of residuals versus fitted values, and the spatial patterns of the predictions matched our observations fairly well. These results, along with the valid ecological relationships of the model, support the conclusion that SS data provide good estimates of lion abundance and distribution.

2. Wildebeest

The wildebeest model had the best performance in the validation process, though large errors possible inflate this measure. The model also has a high proportion of deviance explained. However, I found patterns in the plot of residuals versus fitted values, and the spatial patterns of the predictions did not match our observations. These results, along with the mixed ecological validity of the model, support the conclusion that SS data provide poor to fair estimates of wildebeest abundance and distribution.

3. Topi

The topi model has the highest proportion of deviance explained, and performs reasonably well in the validation process. While I find some patterns in the plot of residuals versus fitted values, the spatial patterns of the predictions match our observations fairly well. These results, along with the mixed ecological validity of the model, support the conclusion that SS data provide fair estimates of topi abundance and distribution.

4. Impala

The impala model performs reasonably well in the validation process, and has a fair proportion of deviance explained. I found some patterning in the residuals, though the spatial patterns of the predictions matched the observations reasonably well. These results, along with the mixed ecological validity of the model, support the conclusion that SS data provide fair estimates of impala abundance and distribution.

5. Elephants

The elephant model had a relatively high proportion of deviance explained, and performed reasonably well in the validation process. I found no patterns in the residuals, and the spatial patterns of the predictions match the observations well. These results, along with the valid ecological relationships in the model, support the conclusion that SS data provide good estimates of elephant abundance and distribution.

6. Buffalo

The buffalo model has a low proportion of deviance explained, despite having the most explanatory variables in the model. The model performs very well in the validation process with TS data, with reasonable errors. However, I find patterns in the residuals, and the spatial patterns of the predictions do not match the observations. These results, along with the valid ecological relationships in the model, support the conclusion that SS data provide fair estimates of buffalo abundance and distribution.

7. Zebra

The zebra model performs reasonably well in the validation process, but with a low proportion of deviance explained. I find patterns in the residuals, and the spatial predictions do not match the observations. These results, along with the mixed ecological validity of the model, support the conclusion that SS data provide poor estimates of zebra abundance and distribution.

8. Grant's gazelle

The Grant's gazelle model performed very poorly in our validation process. However, it has a reasonable proportion of deviance explained, does not show patterns in the residuals, and predicts the spatial distribution of gazelle fairly well. These results, along with the mixed ecological validity of the model, support the conclusion that SS data provide poor to fair estimates of gazelle abundance and distribution.

9. Giraffe

The giraffe model performs well in the validation process, with a reasonable proportion of deviance explained. I do not find any patterns in the residuals, and the spatial predictions match the observations reasonably well. These results, along with the poor ecological validity of the model, support the conclusion that SS data provide fair estimates of giraffe abundance and distribution.

Volunteer Preferences and Motivation

Volunteers under-reported Thomson's gazelle, which are the most abundant species in the OMC according to the TS data. Volunteers in general reported a different set of species than did the TS sampling data. These results support the conclusion that volunteers are more interested in recording species with large body sizes or rare occurrences. A very common species like Thomson's gazelle was perhaps seen as too abundant to bother recording. Volunteers also resisted reporting individuals or small groups of species that occur in large herd sizes; for instance, many wildebeest or topi will be seen roaming singularly or in small groups, but SS observations tended to be of only the larger herds (median TS wildebeest report = 7, median SS wildebeest report = 38). This difference in sampling styles makes comparisons between the two datasets difficult.

Together the sightings of the nine species in our analysis account for 69% of all the SS observations within the study site. While some volunteers indicated they would like to record more than the 29 species we chose for our study, it seems that restricting the range of species sampled to the larger, more charismatic megafauna might make the task seem more feasible and interesting to many of the tourist participants. By focusing on a more limited number of species to record, volunteers will not be constantly entering data throughout their game drive, which participants found to be unappealing. Other studies support the finding that long, arduous, or repetitive tasks are not suitable for citizen scientists (Darwall and Dulvy 1996; Penrose and Call 1995; Dickinson et al. 2010). Previous studies also agree that volunteers perform better when the species of interest are easy to identify (McLaren and Cadmen 1998). I would add that those species should also be easy to count, as volunteers seemed overwhelmed by the number of small gazelles or massive wildebeest herds they were being asked to record. I make further recommendations for increasing participation rates and maintaining volunteer interest in Chapter Two.

Conclusion: The Reliability of Citizen Science

The results of this study indicate that the reliability of CS data varies widely by species and participants, and thus should be assessed on a species and site-specific basis. As the perceived accuracy of SS data was inflated by large errors in the predictions, it is important for evaluations like this one to focus on the suitability and performance of the analytical methods used. Given the tendency for CS data to have considerable errors and biases, I recommend more advanced methods for analysis than GLMs. Unfortunately, some of the more sophisticated methods for analyzing CS data are very challenging to master (Dickinson et al. 2010), which could limit the utility of CS data in the future unless sufficient attention is given towards training ecologists and wildlife managers in these techniques. As CS programs continue to increase in PAs around East Africa, future research should focus on testing the reliability of these data in suitable, site-specific ways if they are to be used to inform management decisions.

Chapter Four | Conclusions Moving Forward

This thesis tested the feasibility, reliability, and utility of citizen science methods for animal monitoring in a small protected area of southwestern Kenya. I address logistical and social problems and prospects for CS in East Africa, highlighting the need for lodges to take ownership over the program and the data produced by it. I use generalized linear models (GLMs) to model the species-environment relationships for nine species of interest, with mixed results within and across species regarding the quality of model performance and ecological inference. By validating these models with an independently gathered dataset, I assess the level of accuracy for CS data ranges from 60-87% for eight out of nine species.

I found that successful CS programs would depend in large part on the administrative staff of the tourist lodges for daily training and maintenance of volunteers and the data they produce. While the directors of the conservancy recognized the potential for CS to produce much-needed data on the distribution of wildlife in the area, the managers on the ground were largely unfamiliar with this kind of monitoring method and remained skeptical as to its feasibility and utility. Managers were hampered by a lack of personal interest in monitoring as well as a lack of time to devote to the program. I found that a successful SS program would likely require full-time staff devoted to program administration, which appears outside the realm of possibility for small conservancies like the OMC. Though it remains untested in this study, I propose that larger lodges with correspondingly larger staff and tourist numbers, might be better suited to this method of monitoring in East Africa. However, similar limitations in manager interest and motivation will likely be a concern at those lodges as well.

Tourists as Safari Scientists showed high variability in their interest and motivation for recording wildlife locations and number throughout their game drives. The short training sessions we used in this study were sufficient for most participants, though volunteers would likely benefit from demonstrations in the field in addition to pre-departure briefings. As many tourists arrive in the region unaware of the severe declines in wildlife populations and the increasing need for more reliable data on their distributions, I propose that future SS programs should begin by managing tourist expectations early on. By incorporating a “research safari” option into the vacation packages being marketed by travel agents and lodge websites, tourists will enter into their safari adventure with a more nuanced understanding of the area they are visiting and a greater enthusiasm for participating in conservation activities like the SS program.

Still, I make several recommendations regarding the level of commitment that should be asked of tourists as citizen scientists. Previous research has shown that long, arduous, or repetitive tasks are not suitable for citizen scientists (Darwall and Dulvy 1996; Penrose and Call 1995), and the feedback from participants in this program indicates that they felt SS required more time than they were willing to give. When any amount of effort is allowed in a CS program, the data produced tend to have high biases such as over-reporting rare species, under-reporting common species, and failure to report repeated sightings (Dickinson et al 2010). For example, in this program, some individuals reported over 100 animal sightings per game drive, while others logged only one or two throughout the course of several hours in the field. By reducing the number of species of interest to animals with larger body size and rarer occurrences, future SS programs may strike a balance between

volunteer interest and the likelihood of acquiring reliable data, though it is not certain those data will be useful for management decision-making. As observer bias and inter-observer variability differ greatly for individual species, it behooves programs like SS to improve their understanding of which species can be reliably reported by citizen scientists.

In testing the reliability of SS data, I relied on GLMs as the most commonly used analytical tool for ecological data that many wildlife managers and ecologists turn to for questions of ecological inference (Rushton et al. 2004). However, this study supports previous work that indicates GLMs are not suitable methods for analyzing CS data, as they do not address the observer error that is particularly pronounced in CS datasets (Elith and Leathwick 2009; Tonachella et al. 2012). I recommend more sophisticated analytical techniques to account for the sampling and observer bias we see in CS data. Generalized Linear Mixed Models (GLMMs) and other hierarchical models offer strong potential for SS data. By including random effects for observers, game drives, driver-guides, and other site-specific characteristics, GLMMs could significantly improve the proportion of deviance explained in SS models of species-environment relationships and thus produce more accurate and reliable results for ecological inference by managers.

This study finds Safari Science a complex and difficult monitoring method to implement in East African Protected Areas. There are significant logistical barriers, primarily the lack of interest or motivation of lodge managers and tourists in participating in these kinds of programs. The analysis of the data produced by SS also presents a challenge to the scalability of such a venture, as the sophisticated modelling methods required will exceed the ability of many ecologists and wildlife managers. Still, the potential for programs like Safari Science remains high, and if people on the ground are active in ensuring the reliability of the data then citizen science may offer an exciting solution to the problem of fine-scale animal monitoring. As the benefits of citizen science increasingly attract the attention of wildlife managers in developing countries, I recommend future programs in East Africa carefully and realistically weigh their ability to address these obstacles before implementing a Safari Science approach to monitoring wildlife.

Tables

| Species Observed |
|---|
| olive baboon (<i>Papio anubis</i>) |
| bat-eared fox (<i>Otocyon megalotis</i>) |
| black-backed jackal (<i>Canis mesomelas</i>) |
| black rhinoceros (<i>Diceros bicornis</i>) |
| African buffalo (<i>Syncerus caffer</i>) |
| domestic cattle (<i>Bos primigenius</i>) |
| cheetah (<i>Acinonyx jubatus</i>) |
| Kirk's dik-dik (<i>Madoqua kirkii</i>) |
| domestic dog (<i>Canis lupus familiaris</i>) |
| domestic donkey (<i>Equus africanus asinus</i>) |
| eland (<i>Taurotragus oryx</i>) |
| African elephant (<i>Loxodonta africana</i>) |
| Masai giraffe (<i>Giraffa camelopardalis tippelskirchi</i>) |
| domestic sheep and goats (<i>Ovis aries</i> and <i>Capra aegagrus hircus</i>) |
| Grant's gazelle (<i>Gazella granti</i>) |
| Thomson's gazelle (<i>Gazella rufifrons thomsoni</i>) |
| Coke's hartebeest (<i>Alcelaphus buselaphus cokei</i>) |
| hippopotamus (<i>Hippopotamus amphibius</i>) |
| spotted hyena (<i>Crocuta crocuta</i>) |
| impala (<i>Aepyceros melampus</i>) |
| leopard (<i>Panthera pardus</i>) |
| lion (<i>Panthera leo</i>) |
| the ostrich (<i>Struthio camelus massaicus</i>) |
| topi (<i>Damaliscus lunatus topi</i>) |
| vervet monkey (<i>Cercopithecus pygerythrus</i>) |
| warthog (<i>Phacochoerus africanus</i>) |
| Defassa waterbuck (<i>Kobus ellipsiprymnus defassa</i>) |
| wildebeest or white-bearded gnu (<i>Connochaetes taurinus albojubatus</i>) |
| Burchell's zebra (<i>Equus quagga boehmi</i>) |

Table1. 29 species were chosen for this study: five domestic species and 24 wildlife species. Neither method recorded any black rhinoceroses.

| | Slope | Distance to Boundary | NDVI | Distance to Lodge | Distance to River | TWI |
|-----------------------------|--------|----------------------|--------|-------------------|-------------------|-----|
| Slope | 1 | | | | | |
| Distance to Boundary | -0.141 | 1 | | | | |
| NDVI | -0.208 | -0.001 | 1 | | | |
| Distance to Lodge | -0.066 | 0.436 | -0.001 | 1 | | |
| Distance to River | -0.063 | 0.161 | -0.169 | 0.509 | 1 | |
| TWI | -0.293 | -0.293 | 0.122 | -0.081 | -0.241 | 1 |

Table 2. Pearson's correlations for all variables used in modeling.

| | |
|-----------------|--|
| Lion | $\log \lambda_i = \alpha + X_{i \text{ dist_river}} * \beta_i + X_{i \text{ TWI}} * \beta_i$ |
| Wildebeest | $\log \lambda_i = \alpha + X_{i \text{ slope}} * \beta_i + X_{i \text{ dist_boundary}} * \beta_i + X_{i \text{ TWI}} * \beta_i$ |
| Topi | $\log \lambda_i = \alpha + X_{i \text{ dist_river}} * \beta_i + X_{i \text{ TWI}} * \beta_i$ |
| Impala | $\log \lambda_i = \alpha + X_{i \text{ slope}} * \beta_i + X_{i \text{ dist_lodge}} * \beta_i + X_{i \text{ TWI}} * \beta_i$ |
| Elephant | $\log \lambda_i = \alpha + X_{i \text{ NDVI}} * \beta_i + X_{i \text{ NDVI}}^2 * \beta_i + X_{i \text{ dist_boundary}} * \beta_i$ |
| Buffalo | $\log \lambda_i = \alpha + X_{i \text{ NDVI}} * \beta_i + X_{i \text{ dist_river}} * \beta_i + X_{i \text{ TWI}} * \beta_i + X_{i \text{ TWI}}^2 * \beta_i$ |
| Zebra | $\log \lambda_i = \alpha + X_{i \text{ dist_lodge}} * \beta_i + X_{i \text{ dist_boundary}} * \beta_i + X_{i \text{ TWI}} * \beta_i$ |
| Grant's gazelle | $\log \lambda_i = \alpha + X_{i \text{ slope}} * \beta_i$ |
| Giraffe | $\log \lambda_i = \alpha + X_{i \text{ dist_lodge}} * \beta_i + X_{i \text{ dist_river}} * \beta_i + X_{i \text{ TWI}} * \beta_i$ |

Table 3. The form of the best models for each species

| | Safari Science | Traditional Sampling | |
|-----------------|----------------|--------------------------|-------|
| Lion | 41 | Thomson's gazelle | 1,314 |
| Wildebeest | 34 | Wildbeest | 896 |
| Topi | 31 | Topi | 700 |
| Impala | 27 | Impala | 610 |
| Elephant | 27 | Zebra | 374 |
| Buffalo | 25 | Grant's gazelle | 244 |
| Zebra | 21 | Warthog | 175 |
| Grant's gazelle | 18 | Domestic cattle | 86 |
| Giraffe | 17 | Domestic sheep and goats | 81 |

Table 4. Number of sightings for the nine most commonly reported species in each method.

| Lion | Mean | SE | 95% Confidence Interval | | |
|--------------------------|---------|--------|-------------------------|--------|---|
| | | | 2.50% | 97.50% | |
| (Intercept) | 1.9311 | 0.7040 | 0.5513 | 3.3109 | * |
| Distance to River | -0.0003 | 0.0003 | -0.0009 | 0.0004 | |
| TWI | -0.0980 | 0.0893 | -0.2730 | 0.0771 | |
| Dispersion factor | 2.63 | | | | |
| Null deviance | 82.79 | 40 df | | | |
| Residual deviance | 77.99 | 38 df | | | |

Table 5. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the lion model. Variables are considered significant (*) if the CI does not include zero. The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Wildebeest | Mean | SE | 95% Confidence Interval | | |
|-----------------------------|---------|--------|-------------------------|---------|---|
| | | | 2.50% | 97.50% | |
| (Intercept) | 9.6684 | 3.3744 | 3.0546 | 16.2821 | * |
| Slope | -0.2497 | 0.1202 | -0.4852 | -0.0142 | * |
| Distance to Boundary | 0.0011 | 0.0005 | 0.0002 | 0.0020 | * |
| TWI | -0.6021 | 0.4640 | -1.5115 | 0.3073 | |
| Dispersion factor | 1015.78 | | | | |
| Null deviance | 30454 | 33 df | | | |
| Residual deviance | 17272 | 30 df | | | |

Table 6. Table 4. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the wildebeest model. Variables are considered significant (*) if the CI does not include zero. The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Topi | Mean | SE | 95% Confidence Interval | | |
|--------------------------|---------|--------|-------------------------|---------|---|
| | | | 2.50% | 97.50% | |
| (Intercept) | -3.2856 | 1.5866 | -6.3953 | -0.1759 | * |
| Distance to River | 0.0028 | 0.0011 | 0.0007 | 0.0049 | * |
| TWI | 0.4650 | 0.1093 | 0.2508 | 0.6793 | * |
| Dispersion factor | 26.04 | | | | |
| Null deviance | 1040.63 | 30 df | | | |
| Residual deviance | 474.65 | 28 df | | | |

Table 7. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the topi model. Variables are considered significant (*) if the CI does not include zero. The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Impala | Mean | SE | 95% Confidence Interval | | |
|--------------------------|---------|--------|-------------------------|--------|---|
| | | | 2.50% | 97.50% | |
| (Intercept) | 0.8628 | 1.4523 | 2.4561 | 3.7094 | |
| Slope | -0.0970 | 0.0599 | -0.0114 | 0.0205 | |
| Distance to Lodge | 0.0008 | 0.0004 | 0.0000 | 0.0016 | . |
| TWI | 0.2260 | 0.1067 | 0.0473 | 0.4351 | * |
| Dispersion factor | 23.76 | | | | |
| Null deviance | 762.26 | 26 df | | | |
| Residual deviance | 488.07 | 23 df | | | |

Table 8. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the impala model. Variables are considered significant (*) if the CI does not include zero. Variables of low significance are noted with (.). The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Elephant | Mean | SE | 95% Confidence Interval | | |
|----------------------|---------|--------|-------------------------|--------|---|
| | | | 2.50% | 97.50% | |
| Intercept | -59.87 | 27.92 | -114.59 | -5.15 | * |
| NDVI | 290.50 | 131.40 | 32.96 | 548.04 | * |
| NDVI ² | -331.40 | 154.60 | -634.42 | -28.38 | * |
| Distance to Boundary | -0.0007 | 0.0003 | -0.0013 | 0.0000 | . |
| Dispersion factor | 7.84 | | | | |
| Null deviance | 273.13 | 26 df | | | |
| Residual deviance | 165.66 | 23 df | | | |

Table 9. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the elephant model. Variables are considered significant (*) if the CI does not include zero. Variables of low significance are noted with (.). The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Buffalo | Mean | SE | 95% Confidence Interval | | |
|-------------------|--------|-------|-------------------------|--------|---|
| | | | 2.50% | 97.50% | |
| (Intercept) | -0.56 | 4.30 | -8.98 | 7.87 | |
| NDVI | -11.69 | 7.91 | -27.20 | 3.82 | |
| Distance to River | -0.002 | 0.002 | -0.005 | 0.001 | |
| TWI | 1.89 | 0.82 | 0.29 | 3.49 | * |
| TWI ² | -0.08 | 0.04 | -0.16 | -0.01 | * |
| Dispersion factor | 54.06 | | | | |
| Null deviance | 1433.2 | 24 df | | | |
| Residual deviance | 1005.7 | 20 df | | | |

Table 10. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the buffalo model. Variables are considered significant (*) if the CI does not include zero. The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Zebra | Mean | SE | 95% Confidence Interval | |
|-----------------------------|--------|-------|-------------------------|---------|
| | | | 2.50% | 97.50% |
| (Intercept) | 2.422 | 1.400 | -0.322 | 5.165 |
| Distance to Lodge | -0.001 | 0.001 | -0.003 | 0.000 . |
| Distance to Boundary | 0.002 | 0.001 | 0.000 | 0.003 . |
| TWI | -0.087 | 0.095 | -0.273 | 0.100 |
| Dispersion factor | 40.88 | | | |
| Null deviance | 841.96 | 20 df | | |
| Residual deviance | 596.11 | 17 df | | |

Table 11. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the zebra model. Variables of low significance are noted with (.). The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Grant's gazelle | Mean | SE | 95% Confidence Interval | |
|--------------------------|-------|-------|-------------------------|---------|
| | | | 2.50% | 97.50% |
| (Intercept) | 1.134 | 0.329 | 0.489 | 1.779 * |
| Slope | 0.086 | 0.031 | 0.025 | 0.154 * |
| Dispersion factor | 2.49 | | | |
| Null deviance | 56.17 | 17 df | | |
| Residual deviance | 38.15 | 16 df | | |

Table 12. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the Grant's gazelle model. Variables are considered significant (*) if the CI does not include zero. The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Giraffe | Mean | SE | 95% Confidence Interval | |
|--------------------------|-------------|-----------|--------------------------------|----------|
| | | | 2.50% | 97.50% |
| (Intercept) | 2.270 | 0.598 | 1.097 | 3.442 * |
| Distance to Lodge | 0.0008 | 0.0003 | 0.0001 | 0.0014 * |
| Distance to River | -0.001 | 0.001 | -0.003 | 0.000 |
| TWI | -0.118 | 0.078 | -0.271 | 0.036 |
| Dispersion factor | 2.01 | | | |
| Null deviance | 37.60 | 16 df | | |
| Residual deviance | 26.02 | 13 df | | |

Table 13. Regression coefficients, standard errors, and 95% confidence intervals (CI) for the giraffe model. Variables are considered significant (*) if the CI does not include zero. The dispersion factor, null and residual deviance, with corresponding degrees of freedom (df) are given below.

| Species | Accuracy (%) |
|------------------------|---------------------|
| Wildebeest | 86.5 |
| Buffalo | 76.8 |
| Lion | 72.7 |
| Giraffe | 68.5 |
| Elephant | 63.6 |
| Impala | 62.5 |
| Zebra | 61.8 |
| Topi | 60.3 |
| Grant's gazelle | 27.9 |

Table 14. Accuracy is determined by the number of TS observations that fell within the 95% confidence interval of predicted values.

Figures

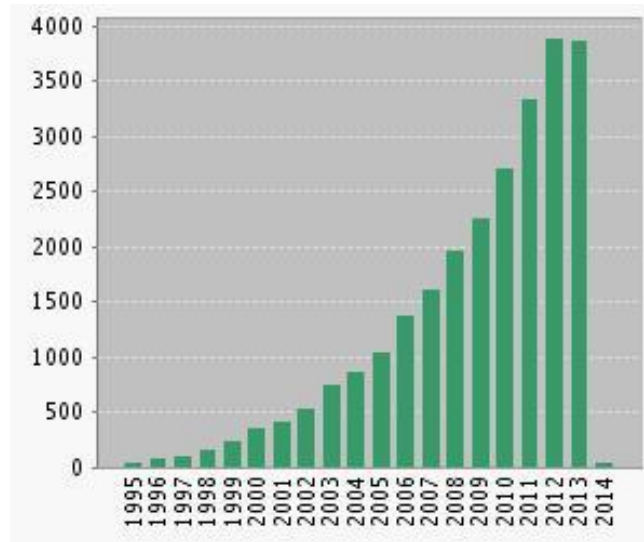


Figure 1. Web of Science citation report for articles pertaining to "citizen science". Citations peaked in 2012 with over 3,800 citations.

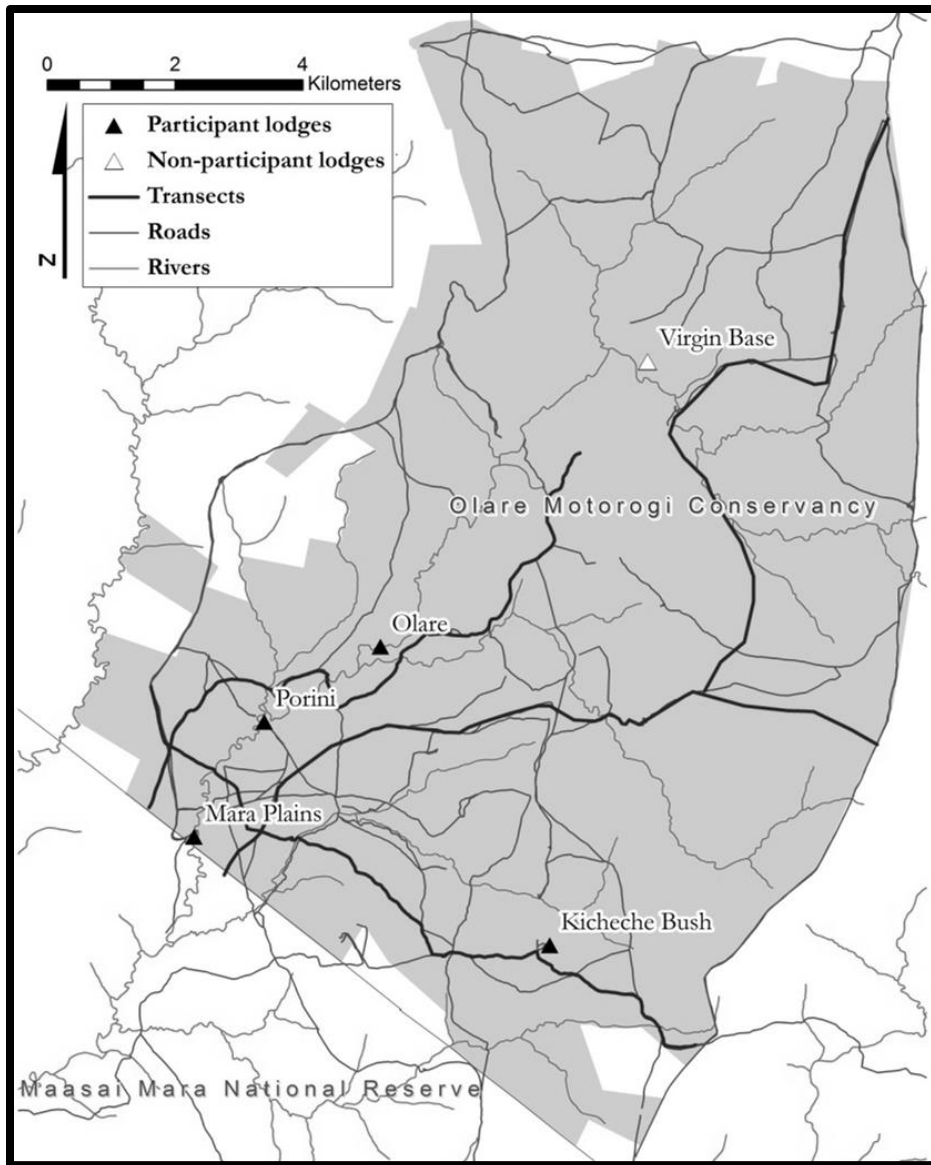


Figure 2. Olare Motorogi Conservancy (OMC) has five member lodges, though only four were available to participate in our study. Four transects were chosen in collaboration with OMC management to maximize coverage while following common roads for tourist game drives.

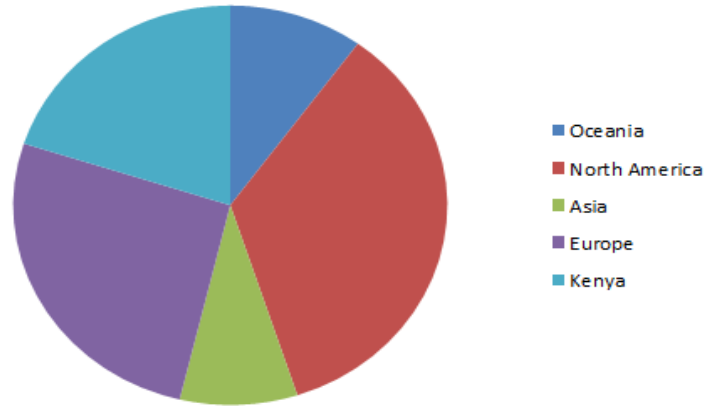


Figure 3. Of the 82 participants, 28 were from North America (US and Canada), 23 were from Europe, 16 from Kenya, 8 from Oceania (Australia and New Zealand), and 7 from Asia.

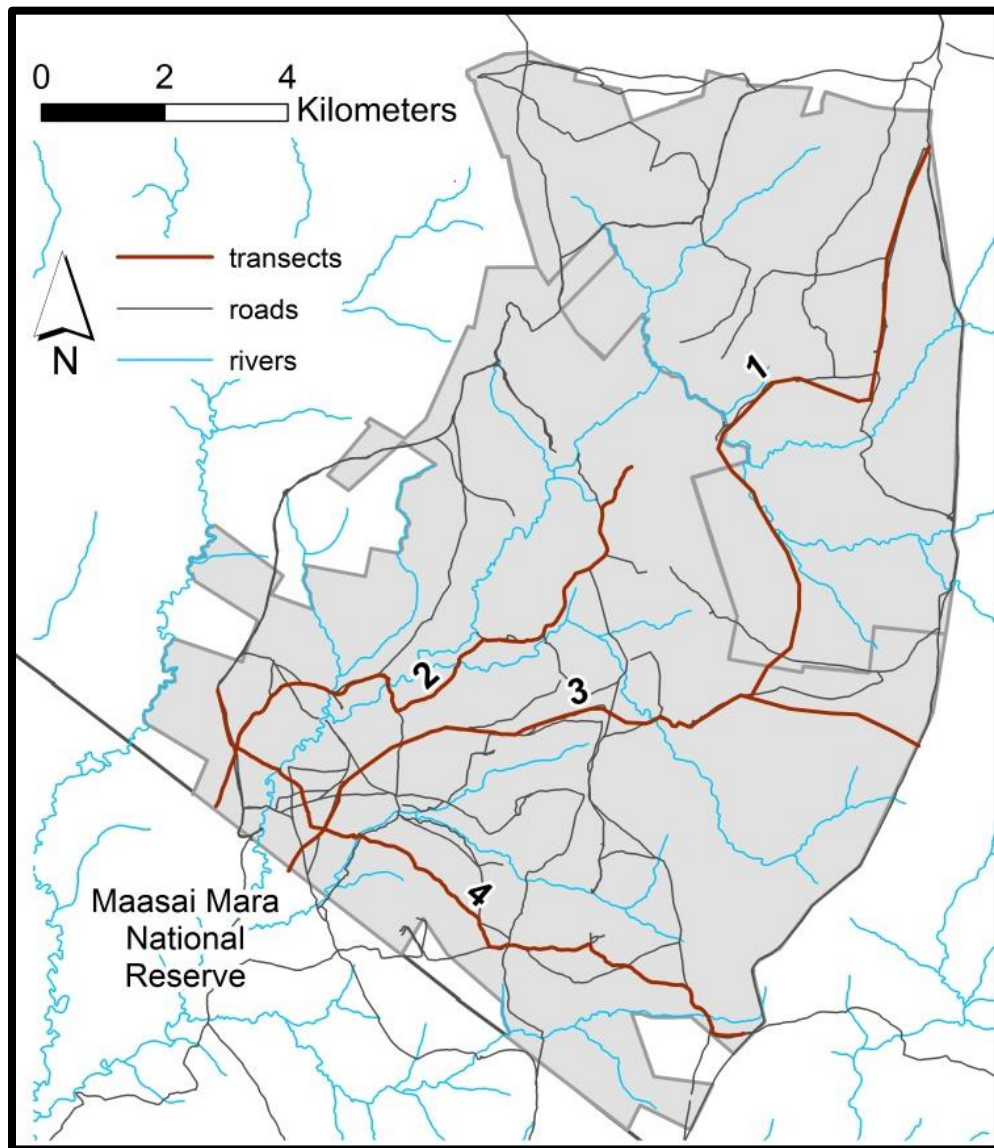


Figure 4. Olare Motorogi Conservancy, with study transects labeled.

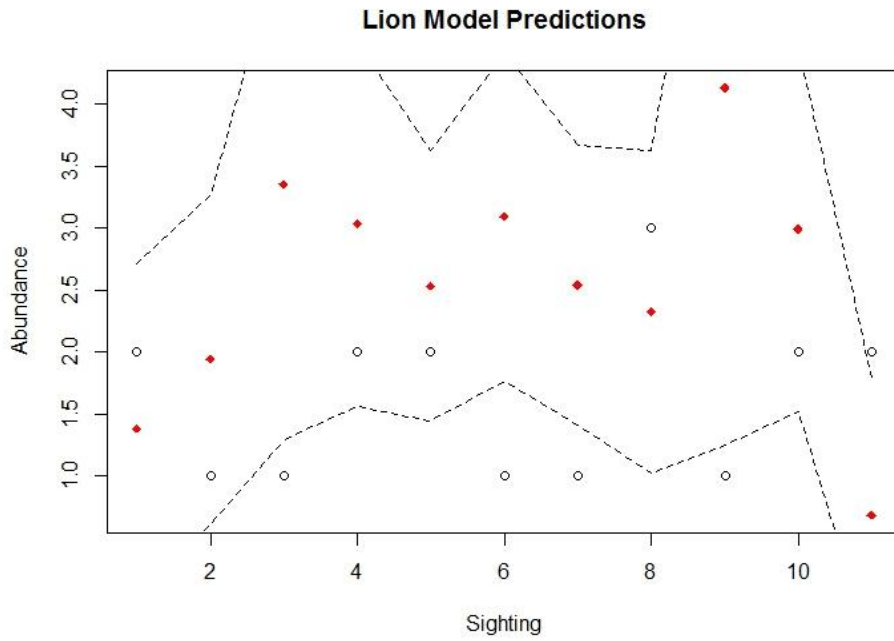


Figure 5. Predicted (red) versus observed (hollow) lion abundances, with the 95% confidence interval (dotted) for the predictions.

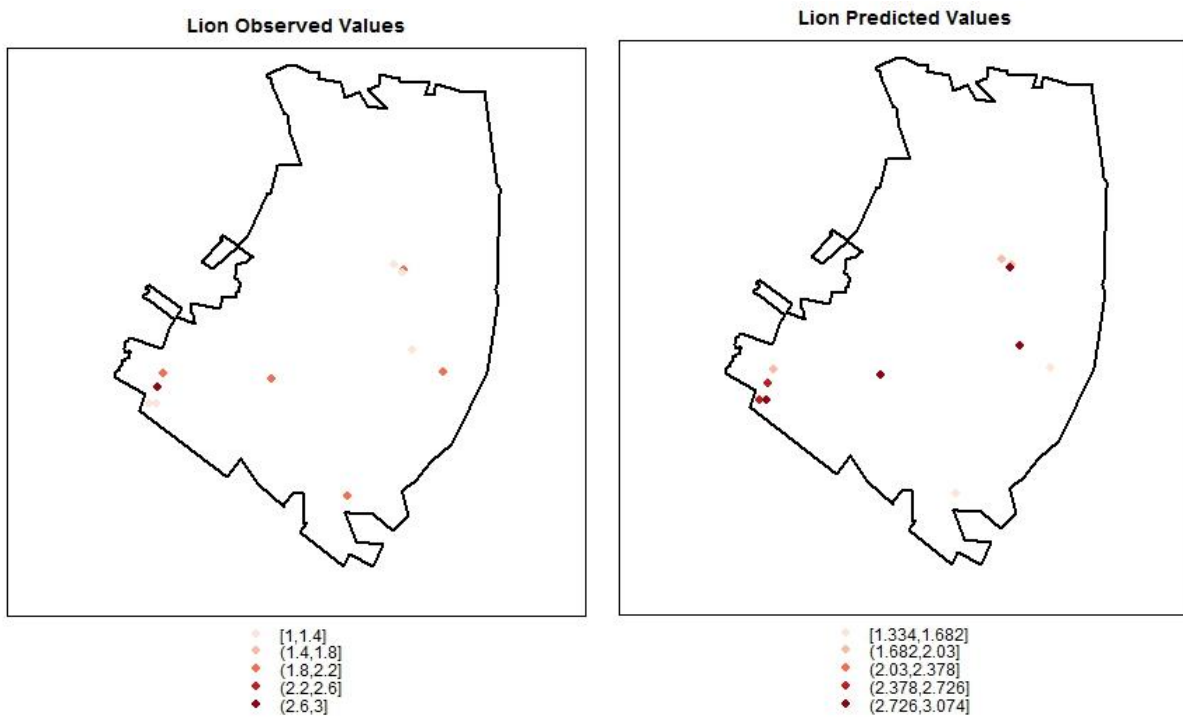


Figure 6. Spatial patterns in observed and predicted lion abundance.

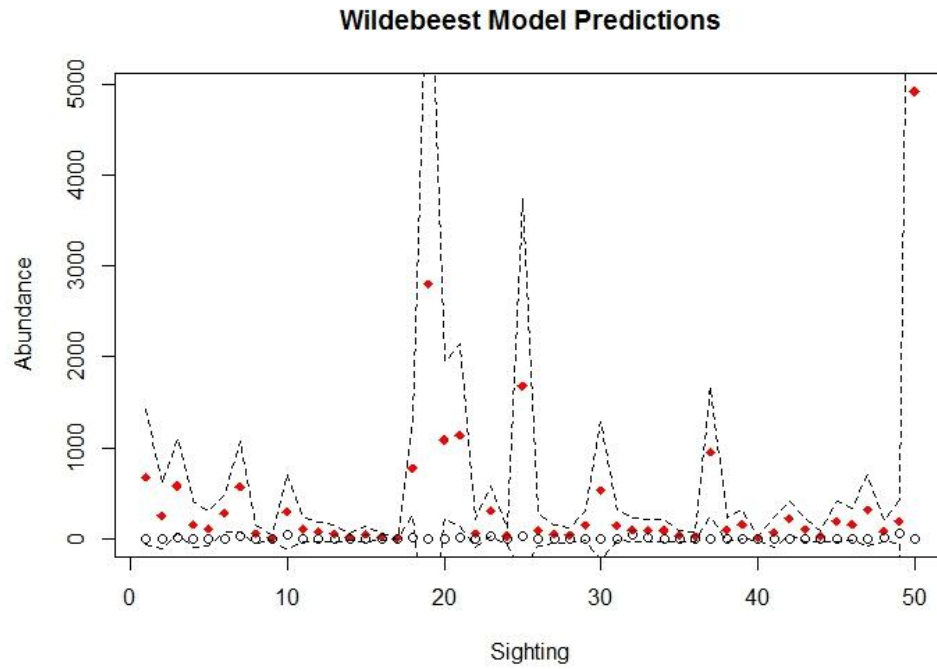


Figure 7. Predicted (red) versus observed (hollow) wildebeest abundances, with the 95% confidence interval (dotted) for the predictions. Graph shows records 1:50 out of 896 to improve interpretation.

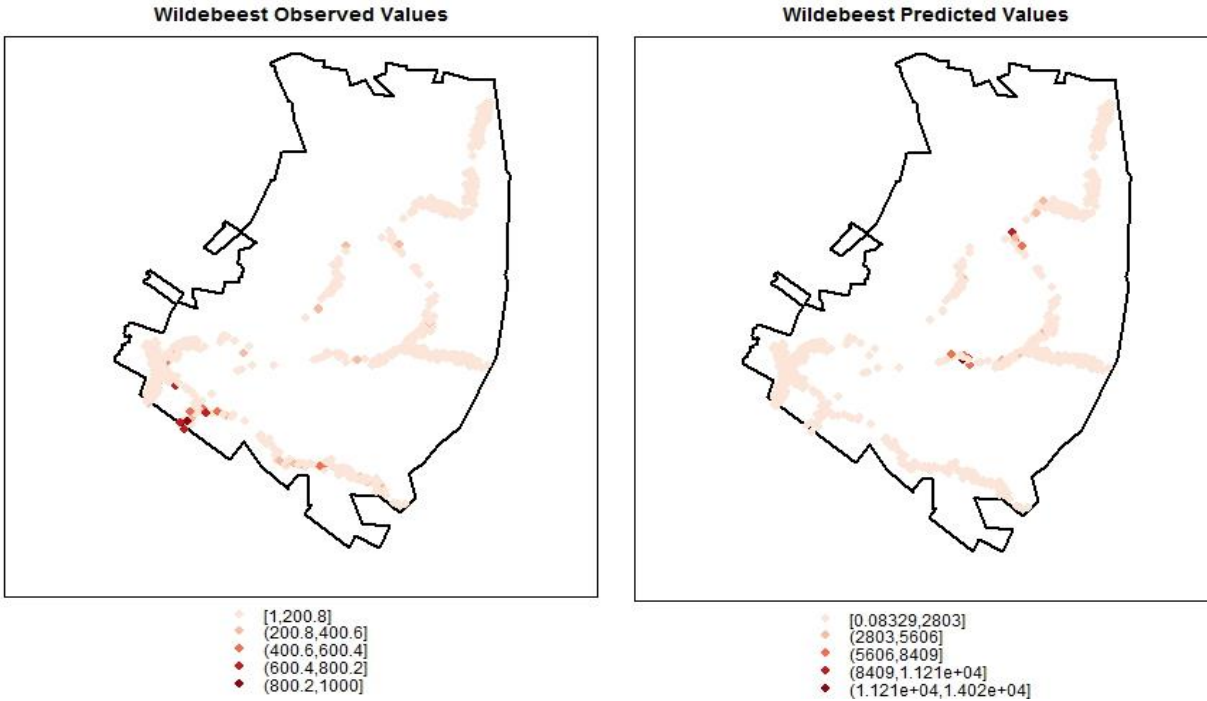


Figure 8. Spatial patterns in observed and predicted wildebeest abundance.

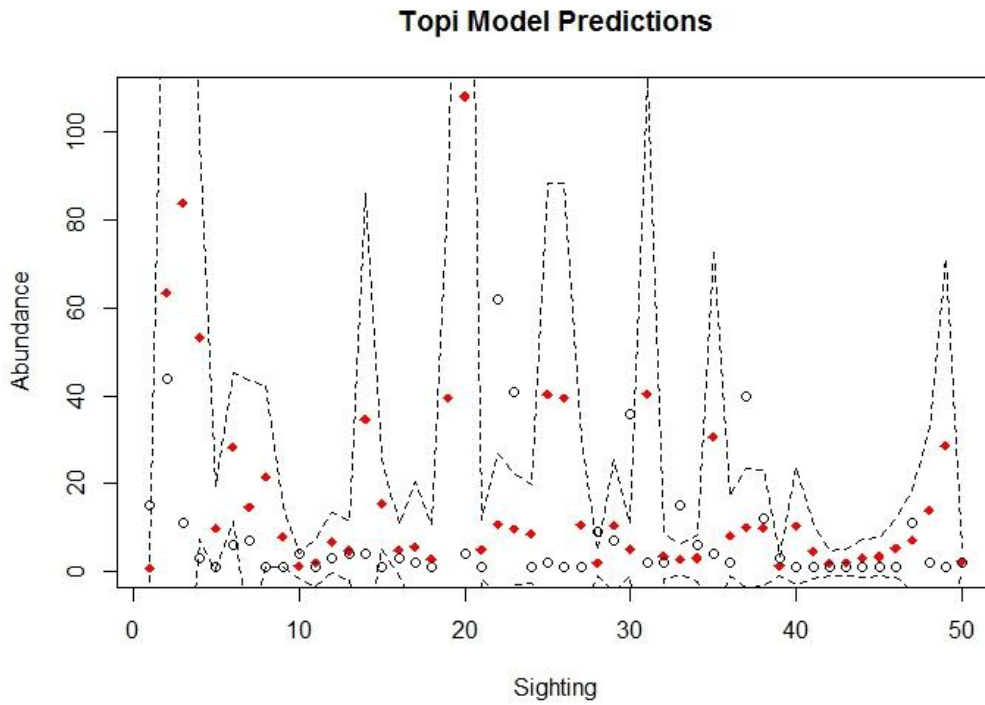


Figure 9. Predicted (red) versus observed (hollow) topi abundances, with the 95% confidence interval (dotted) for the predictions. Graph shows records 1:50 out of 701 to improve interpretation.

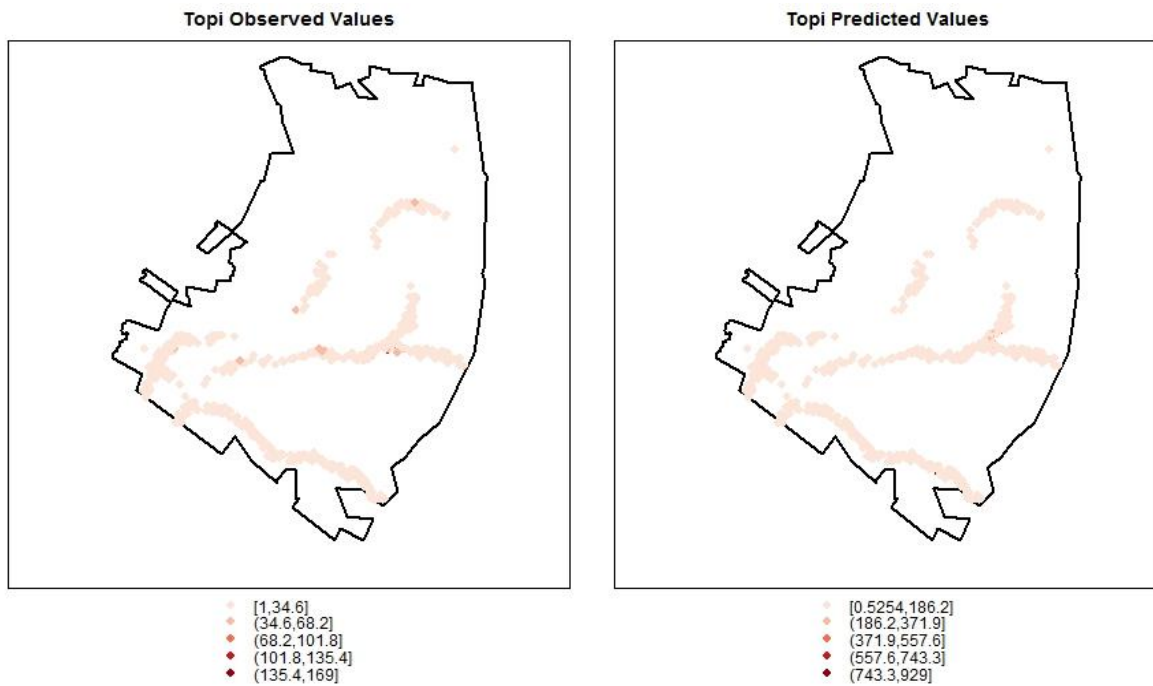


Figure 10. Spatial patterns in observed and predicted topi abundance.

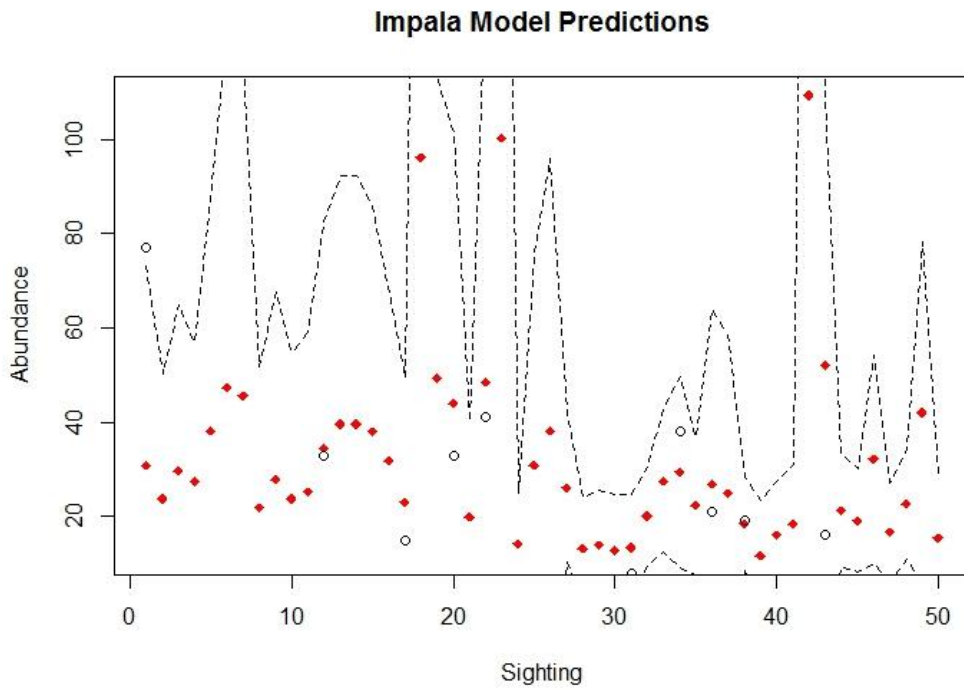


Figure 11. Predicted (red) versus observed (hollow) impala abundances, with the 95% confidence interval (dotted) for the predictions. Graph shows records 1:50 out of 610 to improve interpretation.

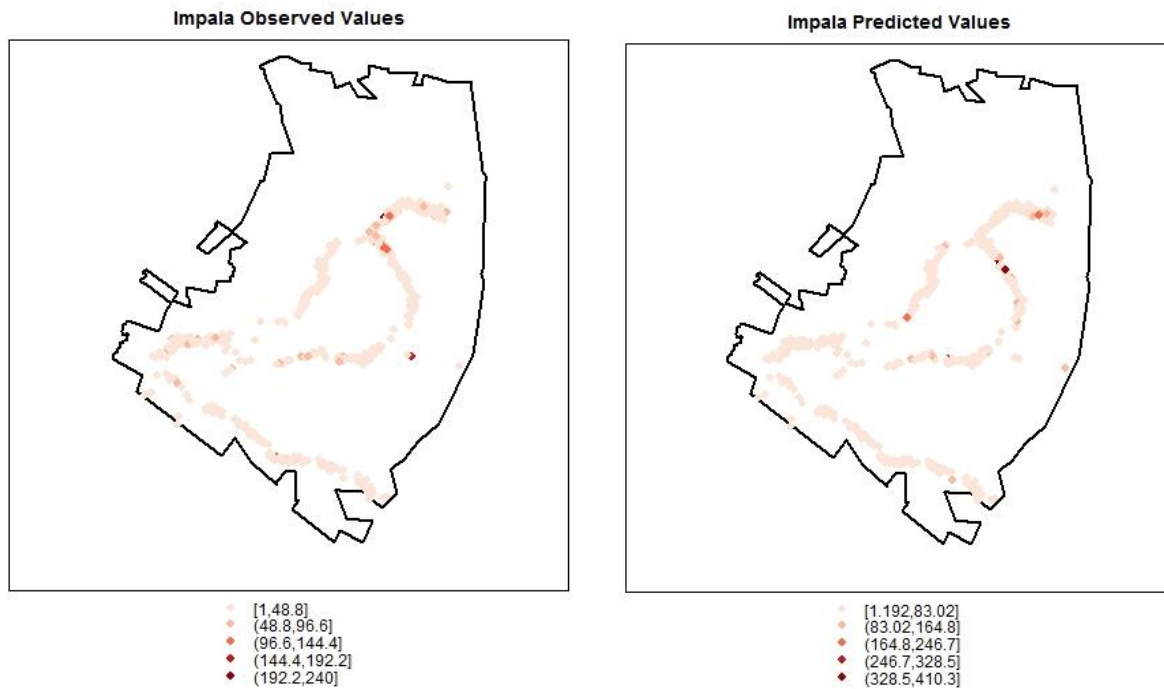


Figure 12. Spatial patterns in observed and predicted impala abundance.

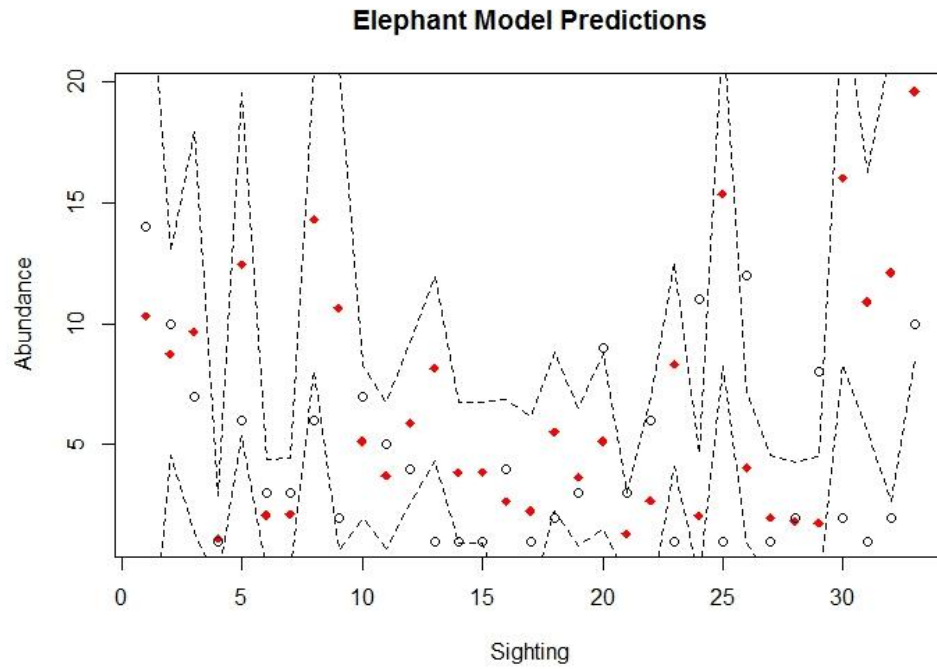


Figure 13. Predicted (red) versus observed (hollow) elephant abundances, with the 95% confidence interval (dotted) for the predictions.

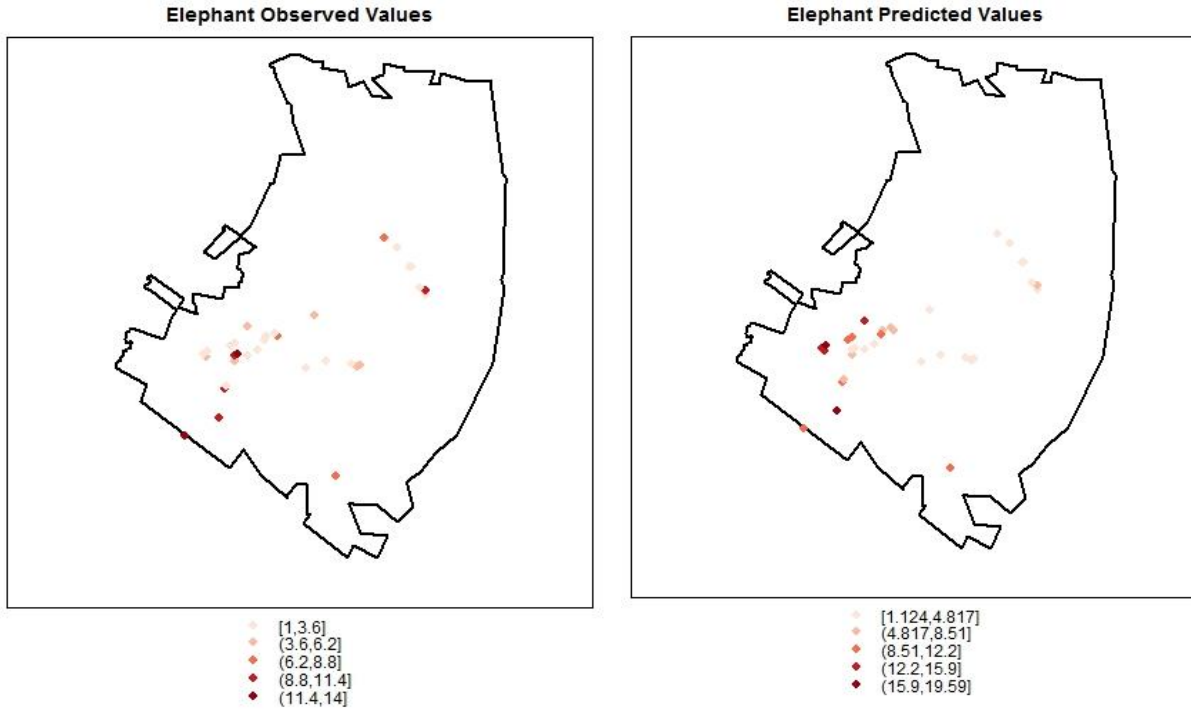


Figure 14. Spatial patterns in observed and predicted elephant abundance.

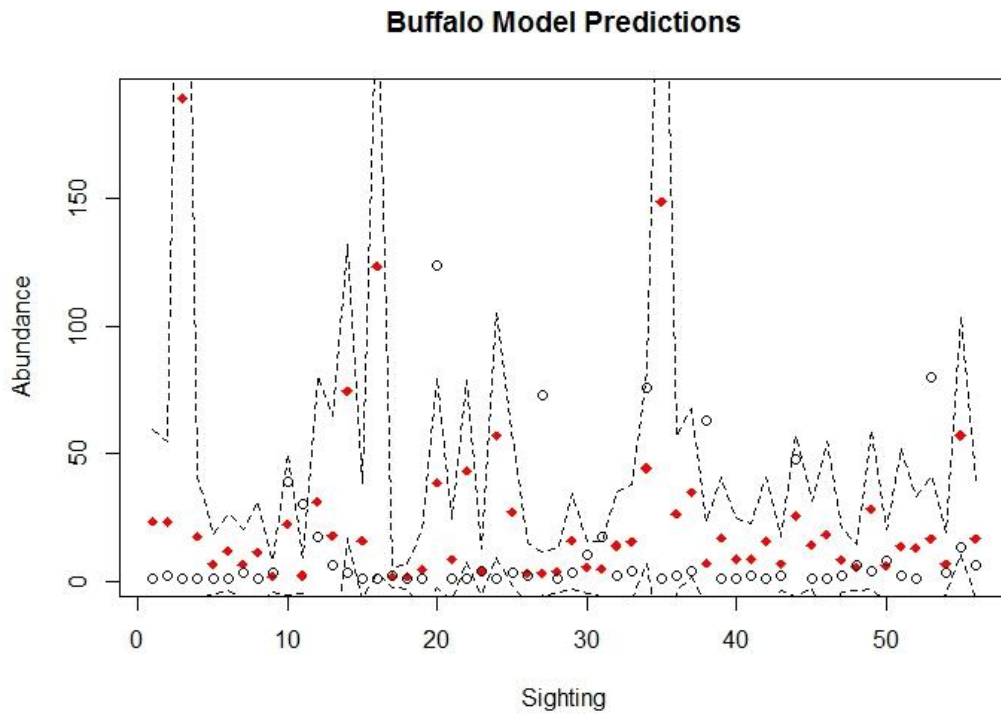


Figure 15. Predicted (red) versus observed (hollow) buffalo abundances, with the 95% confidence interval (dotted) for the predictions.

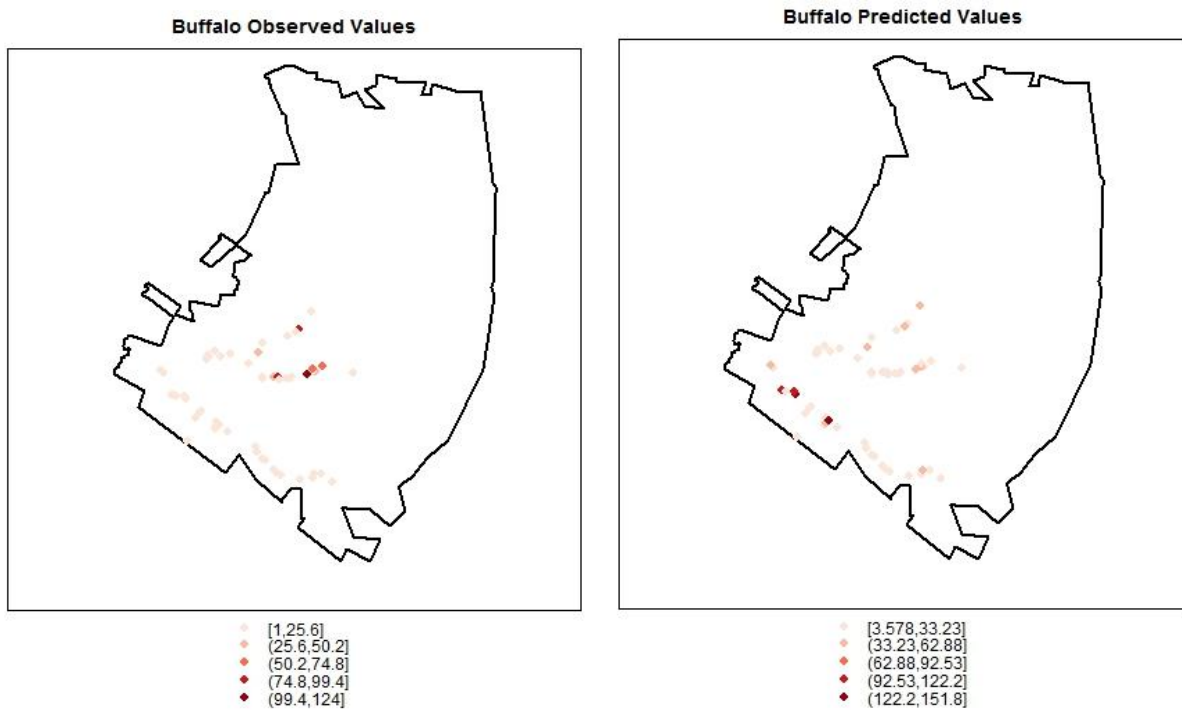


Figure 16. Spatial patterns in observed and predicted buffalo abundance.

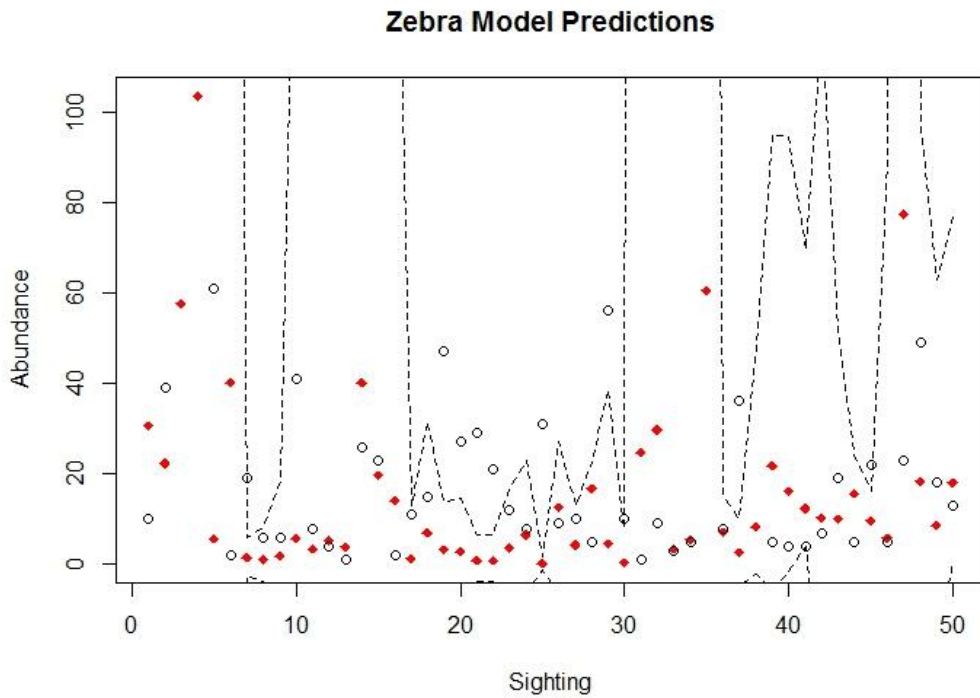


Figure 17. Predicted (red) versus observed (hollow) zebra abundances, with the 95% confidence interval (dotted) for the predictions. Graph shows records 1:50 out of 374 to improve interpretation.

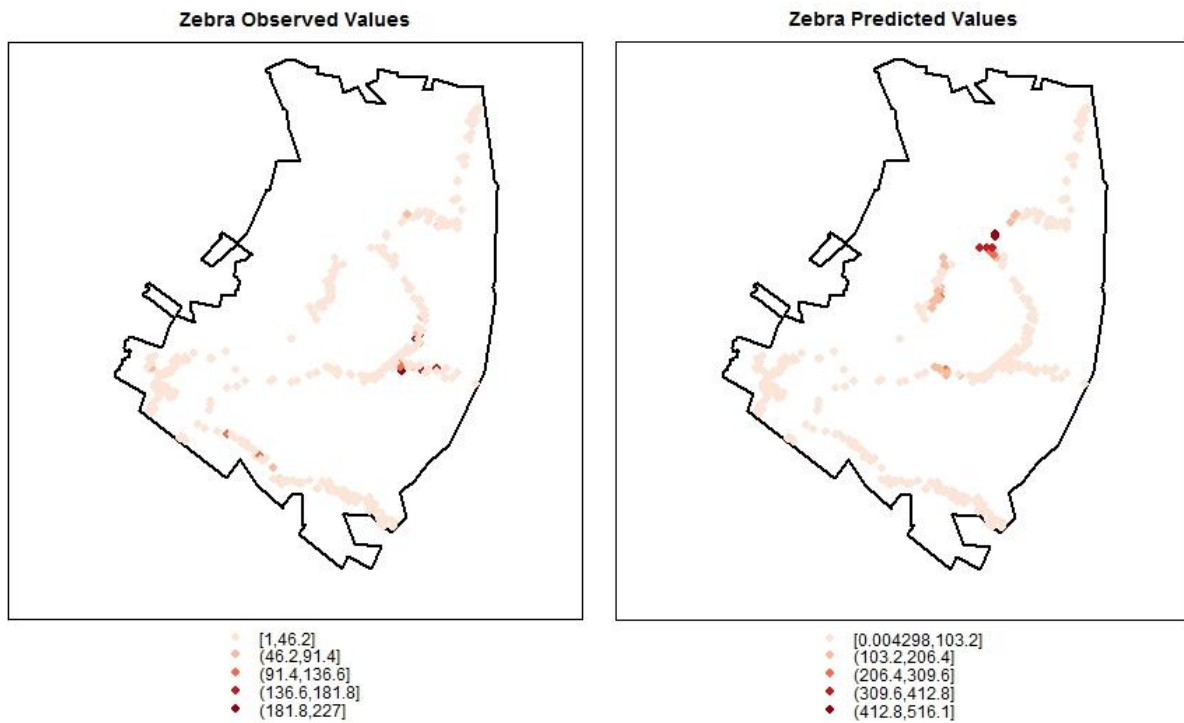


Figure 18. Spatial patterns in observed and predicted zebra abundance.

Grant's gazelle Model Predictions

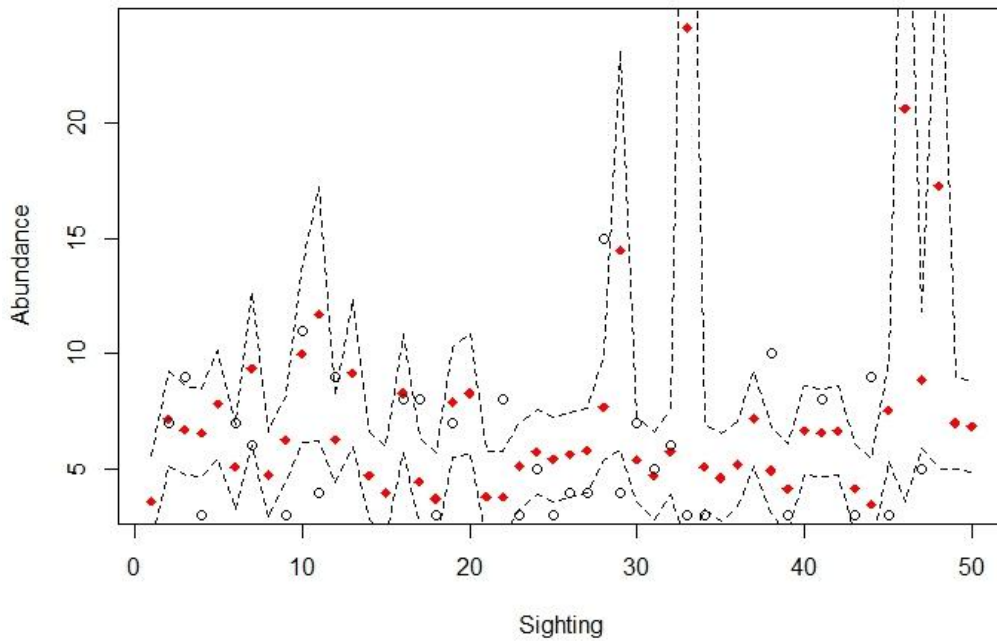


Figure 19. Predicted (red) versus observed (hollow) Grant's gazelle abundances, with the 95% confidence interval (dotted) for the predictions. Graph shows records 1:50 out of 374 to improve interpretation.

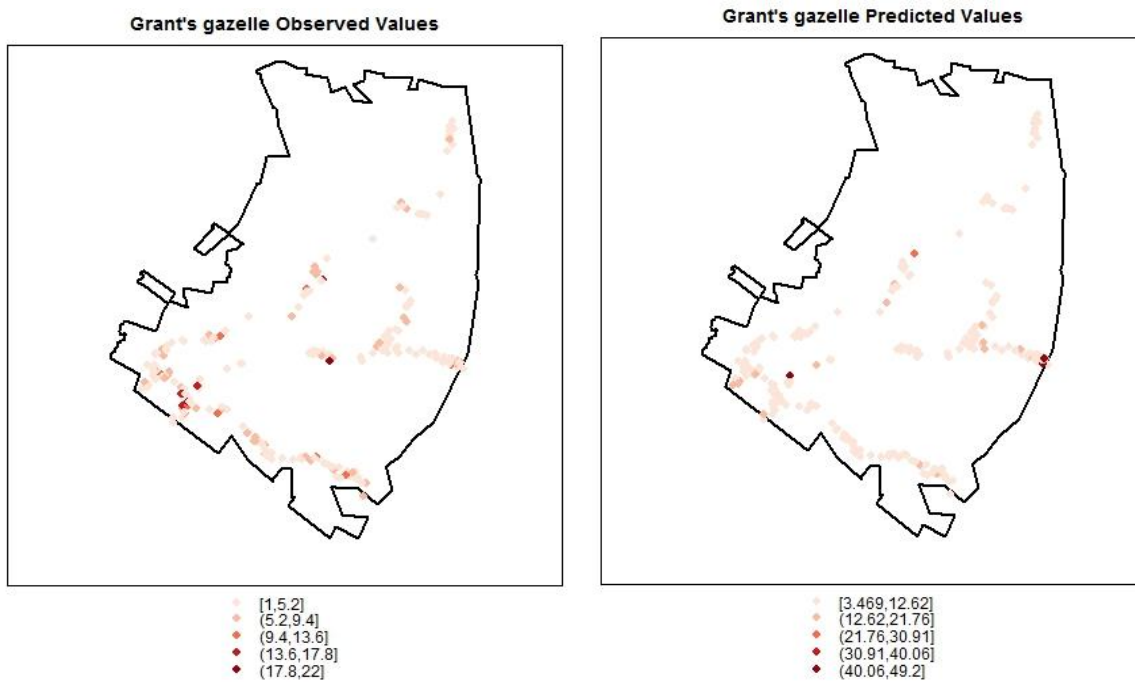


Figure 20. Spatial patterns in observed and predicted Grant's gazelle abundance.

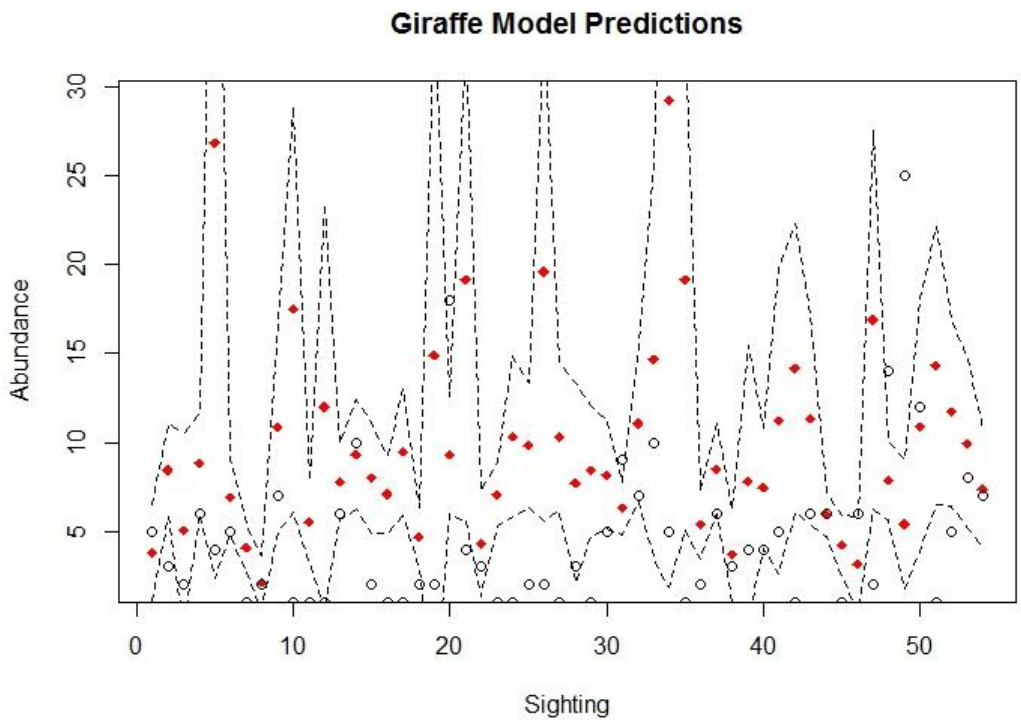


Figure 21. Predicted (red) versus observed (hollow) giraffe abundances, with the 95% confidence interval (dotted) for the predictions.

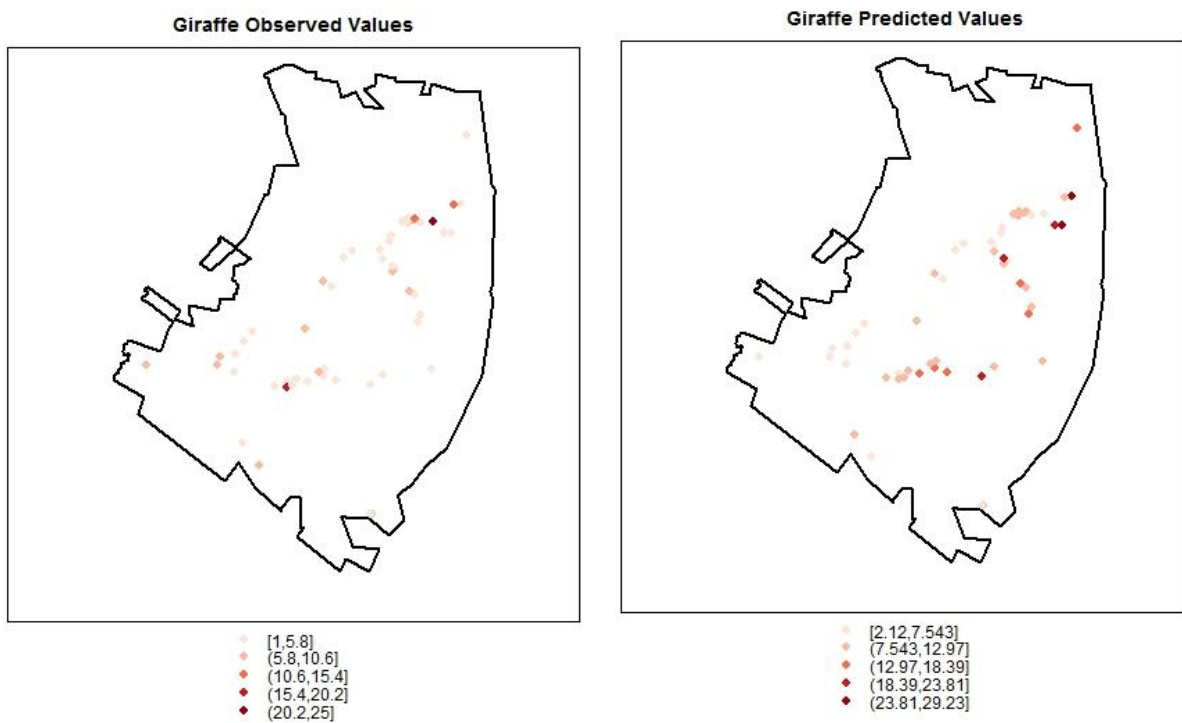


Figure 22. Spatial patterns in observed and predicted giraffe abundance.

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