# The reliability and conservation value of ranger-collected data on elephant poaching

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A dissertation submitted for the degree of Doctor of Philosophy

University of Oxford

December 2020

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## Abstract

Globally, hundreds of thousands of wildlife rangers patrol wide areas within protected areas every day, observing biodiversity and illegal activities. Data collection by rangers therefore has enormous potential to track changes in biodiversity and threats to it, at scale and with little additional cost. However, ranger patrols are biased in space and time and detections are imperfect, so what rangers observe may not capture underlying reality well. Furthermore, even when monitoring results are reliable, they might not be used effectively to inform conservation management. Effective ranger-based monitoring also requires active engagement by the people collecting and using data (rangers and managers). In this Thesis I investigated factors affecting (a) the reliability of ranger-based monitoring data and, (b) the effective use of these data within conservation management. I used the monitoring and management of elephant poaching in the Mana-Chewore World Heritage Site, Zimbabwe, as a case study and combined statistical, mathematical, and qualitative methods.

I began with a participatory modelling approach in which rangers and managers helped me to build and evaluate models of the spatial distribution of elephant poaching in Mana-Chewore, with statistical methods to account for patrol bias. Combining quantitative models and interview responses allowed for more robust inference in the face of uncertainty, with proximity to water emerging as the strongest driver of poaching (reflecting both poacher and elephant behaviour). Next, I developed mathematical simulations to quantify how patrol characteristics (effort, spatial coverage, etc.) interacted with poaching dynamics to affect the power of ranger-collected data to detect underlying spatial and temporal trends in poaching. Power to detect trends was low in many scenarios, with some non-intuitive results (such as spatially targeted patrols achieving power similar to spatially random patrols). Strategies required to achieve robust results depended heavily on monitoring objectives (the magnitude of change in poaching that managers wish to detect, for example). To complement these quantitative insights, I interviewed 23 rangers working in Mana-Chewore to investigate their perceptions of patrol-based data collection. I found that their occupational culture (including a strong sense of duty and deference to authority), as well as their awareness of how their data were used, shaped their engagement with monitoring. In a second qualitative analysis, I interviewed nine park managers and 17 senior staff of the national wildlife authority to investigate the extent to which ranger-collected data were used to inform anti-poaching. Managers valued and made basic use of ranger-collected poaching data but did not systematically analyse trends in these data to inform their anti-poaching strategies. Managers

felt that management based on intuition, experience and more reactive data-use was more familiar and dependable, and therefore did not embrace data-based adaptive management.

For ranger-based monitoring to contribute effectively to biodiversity conservation, practitioners and scientists must acknowledge, understand, and account for uncertainty in both monitoring data and the behaviour of those collecting and using it. Clearly defining monitoring and trend detection goals and critically evaluating the likelihood of achieving these goals is essential, as is meaningfully engaging the perspectives of rangers and managers. More generally, this research demonstrates the importance of interdisciplinarity in the study of socio-ecological systems, and the power of models for both understanding and dealing with the uncertainty inherent in these systems.

# Declaration

I declare that this Thesis is my own work. Contributions by other authors to specific manuscripts published as part of this Thesis are indicated in the "Note on co-authorship" on page 8. None of the work submitted for this Thesis has been submitted, in whole or part, for any previous degree.

**Word count**: 54 105 (Excluding tables, figures, references, and appendices).

# Dedication

I dedicate this Thesis to the wildlife rangers working in the Zambezi Valley, Zimbabwe. The data they have collected on elephant poaching in the region underpins all of the research presented in this Thesis. Their commitment to each other, their families, and the animals for which they act as guardians, fills me with hope.

Three rangers working at my field site, the Mana-Chewore World Heritage site in the Zambezi Valley, northern Zimbabwe. Photographs used with permission from each ranger.

"*What we observe is not nature herself, but nature exposed to our method of questioning*" – Werner Heisenberg, Quantum Physicist

A wildlife ranger at my study site in Zimbabwe records data on an old elephant carcass encountered while on patrol. The protected area in which he works is vast (several thousand square kilometres), so not every poached carcass is found by this 'method of questioning'.

## Acknowledgements

First and foremost, I want to acknowledge the support of my supervisor, Professor E.J. Milner-Gulland. It is abundantly clear how earnestly E.J. cares for her students. I can, without exaggeration, say that I have yet to meet someone as committed to the professional and academic success of other people. One need only ask my wife, parents, or friends to discover how often I have spoken of my thankfulness to EJ for her guidance and care as my supervisor. E.J., thank you for seeing my potential and helping me believe in myself. I am now a far more confident, and able, scientist than I was three years ago. Thank you for the time and care you have put into our meetings, into reading my proposals and drafts, into connecting me with others, and in helping me find my own research direction. Thank you most of all, for your example. I remember reading a blog in which you said you loved your work as an academic, which I must admit surprised me! I guess I was very aware of the insecurity, competitiveness, and pride so often associated with academia. I have learnt from you that the science itself, the people I work with, and the biodiversity we love to study and protect, should take precedence over my own personal success. E.J., as soppy as it sounds, I can honestly say that no other person has had as large an impact on my professional development as you have.

To Danica, my precious wife, your love and commitment to me over the last three years have been unmatched. You know the depth of personal struggle I faced in the first and second year of this DPhil as I battled with a second episode of depression. Your wisdom and compassion carried me through. Your practical and personal support have been essential in getting me to this point. I t was awesome having you with me on my first field trip. You have always been more practical than me and your 4x4 driving skills and general field know-how made all the difference, allowing me to focus on data collection. Thank you also for helping me make difficult decisions during my research, and for looking at countless graphs and sentences to see if they made sense! Thank you most of all for believing in me, and for making it so clear how much you love me.

To my family, thank you for taking such an interest in my work. Mum, thank you for driving me around to interviews in Harare, for connecting me with helpful contacts, for sitting in long queues to buy me petrol for field work, and for packing a trunk of delicious supplies for the field. Thanks for your enthusiasm about my work, and for helping me believe that I had something valuable to contribute. Thanks also for being a sensitive ear during my battle with depression. Finally, thanks for joining me for my second field trip to Mana-Chewore - that was a lot of fun! Papa, thank you for stretching me academically with our many research-related conversations. Thanks particularly for exciting me about the social sciences, helping me design my interview guides, and for helping me understand and interpret my results. Wonderfully, you were just as comfortable talking about the more mathematical element of this work, and you were the toughest critic of my mathematical models. Thank you also for helping me to take a step back and reflect on my role as a researcher and think wisely about how I interact with others and pursue my goals. Now all that is left is to take up your challenge and gain a Professorship at a younger age than you did (though I don't think I have much time!). Saskia, the coolest sister in the world, thanks for moving to England! It has been such a joy to have you and Noah nearby. Thank you for the many fun weekends over the last year and for helping me take my mind off things. Thanks also for your example of perseverance and faith in the face of adversity, which has been an encouragement to me during my DPhil. To Dirk, Lara, Jay and Kate – thank you for your excitement about my research and for your frequent prayers. Thanks also for helping me remember the lighter side of life! Matt Wijers, you feel like family and have been a brother on this academic/conservation journey since 2013. Thank you for making me think and laugh, for understanding me, and praying for me. Wijers & Kuiper Ltd. coming soon!

To my friends and the broader community at St Ebbes Church. Thank you so much for being a home away from home and for helping me keep perspective during my DPhil. Glenn, Vaughan, and the other leaders, thank you for helping me to see my work as part of a much bigger picture, one of hope and purpose. To my dear friends Jon Chan and Steven Firmin, thank you for working alongside me on your own DPhil journeys. You both listened to me when I was banging my head against the wall with my research and helped me pick myself up. Jon, you listened so attentively to my research proposals and ideas and helped think through it all, despite not being a real scientist (forgive me ☺). Steven, you pulled me aside when I was running around like a headless chicken and tried to sing me songs to cheer me up. I remember the week you came every morning to make sure I got out of bed and sat with me writing out a work plan each day. Yes, I was that weak at a point! Chris Morton, our endless walks through Oxford were a true sense of refuge for me. I loved listening to your ideas on everything from elephant poaching to following Christ. As someone who had trodden the PhD journey yourself, you were a source of wisdom and clarity on many an occasion.

To my friends and colleagues at the Interdisciplinary Centre for Conservation Science (ICCS), what a joy it has been to get to know you all and learn from you. Melissa, it was invaluable starting our DPhils at the same time, facing the highs and lows together. Thank you for your listening ear, your encouragement, and your wise advice. Tom, thank you for making me laugh and for making me think! Munib, thanks for the cricket and engaging conversations. Rod, thanks for the tennis – one day I will beat you! To the team as a whole, thank you for the many stimulating and at times fiery conversations and debates. You have expanded my worldview.

To my colleagues in Zimbabwe, thank you for helping me ground my work. Nobesuthu Ngwenya and Blessing Kavhu, thank you for your advice in the field and for your valuable contributions to my write ups. Nobesuthu, thanks for helping me plan our future work. Richard Maasdorp and Lynne Taylor, thank you for your unique local knowledge and insights when I was still wet behind the ears. Prof. Victor Muposhi, thanks for your Oxford visit and for helping me plan my fieldwork. Prof. Edson Gandiwa, thanks for your unique perspectives.

To Andy Dobson, thanks for being an excellent mentor for my mathematical modelling and R coding. To Francis Massé, thank you for your kind help with understanding and framing the results of my interviews with rangers.

Finally, to God. You have given me rest from my strivings, grace for my many failings, and an identity that runs deep. You have reminded me again and again that you care for your creation and delight in science, giving direction and meaning to my research. You know and see all things – I am very glad you are not my examiner!

# Note on co-authorship of selected Chapters

Three of my Thesis Chapters involved co-authorship with other scientists as well as my supervisor. As the primary author and DPhil student, I confirm that I contributed the majority of the work for each of these Chapters. That is, I conducted all analyses, and wrote the first draft of each Chapter. Co-authors helped with conceptualisation and writing of drafts as detailed below.

*Chapter 3: Rangers and modellers collaborate to build and evaluate spatial models of African elephant poaching.*

This Chapter has been published in the journal *Biological Conservation* (see the Thesis overview in Chapter 1 for publication details) and involved several co-authors who work with the Zimbabwe Parks and Wildlife Management Authority: Mr Blessing Kavhu, Mrs Nobesuthu Ngwenya, and Mrs Roseline Mandisodza-Chikerema. These authors played a role in project conceptualisation and methodology and helped review drafts.

*Chapter 4: Rangers and modellers collaborate to build and evaluate spatial models of elephant poaching.*

This Chapter involves co-authorship with Dr Andrew Dobson, a postdoctoral researcher at the University of Edinburgh. Dr Dobson provided skills-focussed mentorship as I developed the mathematical model underpinning this Chapter. He also provided comments on earlier drafts.

*Chapter 5: Ranger perceptions of, and engagement with, monitoring of elephant poaching.*

This Chapter has been published in the journal *People and Nature* (see the Thesis overview in Chapter 1 for publication details) and involved co-authorship with a postdoctoral researcher from the University of Northumbria (Dr Francis Massé), as well as three co-authors who work with the Zimbabwe Parks and Wildlife Management Authority: Mr Blessing Kavhu, Mrs Nobesuthu Ngwenya, and Mrs Roseline Mandisodza-Chikerema. Dr Masse helped with the framing of this Chapter and helped edit drafts. Kavhu, Ngwenya, and Chikerema played a role in project conceptualisation and methodology and helped review drafts.

*Other publications:* I also co-authored the following manuscripts while a DPhil student:

Dobson, ADM., Milner-Gulland, EJ., Aebischer, NJ.,…,Kuiper, T.R. et al. (20 or more authors). 2020. Making messy data work for conservation. *One Earth*.

Kuiper, T., Dickman, A. J., Hinks, A. E., Sillero-Zubiri, C., Macdonald, E. A., & Macdonald, D. W. 2018. Combining biological and socio-political criteria to set spatial conservation priorities for the endangered African wild dog. *Animal Conservation*, 1–11.

Kuiper, T. R., Druce, D. J., & Druce, H. C. 2018. Demography and social dynamics of an African elephant population 35 years after reintroduction as juveniles. *Journal of Applied Ecology*, 55.

# Contents

# Chapter 1: Thesis Introduction

## 1.1. Background to research

*Managing biodiversity when monitoring and implementation are uncertain*

The appeal for evidence-based management of natural resources is ubiquitous (Gillson et al., 2019; Sutherland et al., 2004). Central to this is conservation monitoring - collecting and evaluating baseline data on the ecological and social dimensions of the system under management. Protected area managers, for example, need timely and reliable information on threats to the biodiversity under their jurisdiction as an essential baseline for assessing management performance and designing management strategies (van Wilgen and Biggs, 2011). This includes basic data on where in the landscape illegal activities are more likely, and how the intensity of these activities change over time (Critchlow et al., 2015). Conservation-relevant monitoring data, such as information on elephant poaching levels before and after an ivory trade ban are, however, difficult to collect at relevant scales. Measuring and managing socio-ecological systems is challenging because these systems are characterised by dynamic and uncertain linkages between human actors and ecological processes (Ban et al., 2013). Rather than ignoring uncertainty or making simplifying assumptions about it, conservation scientists can better inform effective management of biodiversity by explicitly quantifying and incorporating uncertainty into their research questions (Milner-Gulland and Shea 2017). Conservation managers and policy makers must similarly endeavour to make decisions that are not only evidence-based, but robust to uncertainty (Bunnefeld et al., 2017).

Uncertainty comes in many forms, such as epistemic uncertainty due to our imperfect knowledge of socio-ecological systems, ontological uncertainty due to the inherent complexity of these systems, and strategic uncertainty about how to manage these system well (Dewulf and Biesbroek, 2018). Natural variation in ecological systems, such as the environmental stochasticity affecting species population dynamics, is another important source of uncertainty (Regan et al., 2002). Regan et al. (2002) further identify uncertainty in the vague and ambiguous language used to describe ecological systems (linguistic uncertainty), such as ‘vegetation cover’ and ‘endangered’ which are broad terms open to interpretation. ‘Implementation uncertainty’ may also occur when resources users (e.g., fishers or hunters) do not comply with conservation management rules, or respond to them in unexpected ways (Fulton et al., 2011). These various forms of uncertainty mean that the outcomes of management interventions are unpredictable. It is crucial, therefore, to explicitly acknowledge uncertainty and pursue management pathways that are not only theoretically effective, but also robust to uncertainty (Regan et al., 2005). In this Thesis, I have identified observation uncertainty (a form of epistemic uncertainty) and implementation uncertainty (a form of strategic uncertainty) as particularly relevant to my case-study of ranger-based monitoring.

Observation uncertainty arises from the difficulty of accurately monitoring socio-ecological systems. Monitoring trends in plant and animal populations, and threats to these populations, is essential to understanding how human activities affect natural systems, and to evaluating the effectiveness of interventions designed to protect biodiversity (Canessa et al., 2015; Nichols and Williams, 2006). Yet socio-ecological systems are only partially observable. Field methods to derive real-world data are inevitably constrained by their spatial or temporal extent, or biased in some other way (Dobson et al., 2020; Grimm, 1999). Metrics of biodiversity, as well as measures of human resource use (especially when illegal; Gavin et al., 2010), are often biased and imprecise. As an example, McConville et al. (2009) found that aerial surveys in Kazakhstan underestimate saiga antelope (*Saiga tatarica*) abundance when population density is low, leading to overestimation of rates of decline and confounding managers' ability to accurately measure progress towards conservation goals. It is crucial, therefore, that observation uncertainties like this are understood before inferences about underlying system dynamics are made (quantitative models are a key method for achieving this, as described in the methods overview in Chapter 2). Similarly, it is essential to evaluate whether monitoring programmes have a realistic chance of robustly detecting changes in the environmental variables of interest (Field et al., 2007).

Another, poorly understood, source of uncertainty occurs when conservation policy is translated into practice. Conservation interventions are not implemented in a vacuum; whether or not they achieve their goals depends to a large extent on the values, motivations and broader socio-political context of the people who implement these interventions and the people who are affected by them. The success of the ranger-based monitoring and adaptive management programmes investigated in this Thesis, for example, depend on the priorities and practices of the individual rangers and park managers responsible for collecting and using conservation monitoring data. The drivers of implementation uncertainty typically lie within the remit of social science, so this form of uncertainty is underrepresented in the natural resource management literature (Bunnefeld et al., 2011). A major source of this uncertainty is human behaviour; people do not behave as policymakers or those designing conservation projects envisage. In their comprehensive analysis, for example, Fulton et al. (2011) identified human behaviour as the main source of uncertainty in fisheries management globally.

Furthermore, the relationship between evidence (e.g., ranger-collected data on elephant poaching) and policy (e.g., new anti-poaching strategies) may be messier than much of the evidence-based conservation literature acknowledges. Diverse social and political factors interact with evidence to shape decisions, so real-world policy may be better described as "evidence-informed" rather than "evidence-based" (Adams and Sandbrook, 2013). Nuno et al. (2014), for example, investigated uncertainties in the implementation of strategies to reduce bush meat hunting in the Serengeti, Tanzania, finding that institutional barriers and the influence of key individuals affected implementation success. Conservation interventions in developing countries may be particularly vulnerable to implementation failure due to lack of capacity and resources, and generally weaker governance (Smith et al., 2003). Qualitative research methods are needed to better understand implementation uncertainty in general, and the behaviour and context of rangers and park managers in particular (see the methods overview in Chapter 2).

*The potential of ranger-based monitoring for biodiversity conservation*

The collection of biodiversity data by wildlife rangers, whose job it is to protect threatened species, presents a model case of both the value of monitoring data and the uncertainties inherent in its collection. In this Thesis, I use the term 'ranger' to refer to 'a field-based operative whose regular work involves surveillance, protection and maintenance of species and ecosystems' (Belecky et al., 2019). I define ranger-based monitoring as the collection of data by rangers, which may include evidence of illegal activity, animal sightings and behaviour, and vegetation status (Gavin et al., 2010). While "law-enforcement monitoring" is another common term in the literature for ranger-based monitoring (Moreto et al., 2014; Stokes, 2010), I considered this terms to be too specific to the monitoring of illegal activities.

Globally and daily, hundreds of thousands[1] of rangers patrol large distances within protected areas, observing biodiversity and illegal activities. Ranger-based monitoring thus has significant potential to inform conservation, at large scales and low cost. For example, ranger-based monitoring of illegal activities in the Virunga-Bwindi forests provides large quantities of

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[1] Based on personal communication with Mohammad S. Farhadinia who is compiling a global database of numbers of state-employed rangers.

management-relevant data that influence strategies to reduce threats to gorillas (Gray & Kalpers, 2005). Similarly, careful analysis of ranger-collected data on several types of illegal activity in a Ugandan protected area helped scientists and managers design patrol strategies that led to significant improvements in law enforcement effectiveness (Critchlow et al., 2016). Moore et al. (2018) used 10 years of ranger-collected data on poaching activities in a Malawian protected area to identify areas of high poaching threat, and to demonstrate the effectiveness of patrols at deterring these threats over time, while Ihwagi et al. (2015) used ranger detections of elephant poaching to assess the effectiveness of different land-use policies for elephant protection. As another example, the case study that I investigate in this Thesis is part of a global programme under which ranger-collected data on elephant carcasses from over 60 African protected areas are used to estimated continental poaching rates and trends and inform ivory trade decisions (CITES Secretariat, 2019).

There are three main reasons why ranger-based monitoring can make a significant contribution to the evidence base of what does and does not work in biodiversity conservation. The first is the vast temporal and geographical reach of ranger-based monitoring, leading to potentially large volumes of data. Rangers operate in protected areas across the world, and a high proportion of their time is spent out in the field covering wide areas on a regular basis (Belecky et al., 2019). Their data-collection potential is thus enormous. Secondly, ranger-based monitoring may be cost-efficient compared to independent and systematic biodiversity surveys usually carried out by professional ecologists. Such surveys are skill intensive, and costs often prohibit their use at large spatial and temporal scales, especially in developing countries where resources for biodiversity conservation are limited (Jones et al., 2017). Thirdly, ranger-based monitoring involves a closer link between data collectors and data users. Both wildlife rangers and protected area managers typically work within the same branch (e.g., management and operations) of the same organisation (e.g., the state wildlife department). Such a link, which is absent when monitoring is conducted by external scientists and ecologists, may foster greater integration of monitoring results into local management decisions (Danielsen et al., 2009).

*Implementation and observation uncertainty in ranger-based monitoring*

Against these advantages, however, ranger-based monitoring may be particularly vulnerable to the observation and implementation uncertainties described above. Ranger patrol coverage is almost always biased in space and time, and detections are imperfect, so what rangers observe does not always correlate well with true underlying system dynamics (Dobson et al., 2020). As a result, it is often difficult to know whether observed trends in ranger-collected data reflect changes in the pattern and efficiency of patrol themselves, or real changes in biodiversity or illegal activities. Furthermore, because the relationship between patrol effort and detectability is not constant (with detection efficiency or 'catchability' varying across time and space), even catch-per-unit-effort indices may be biased (Keane et al., 2011). In a study of ranger-based monitoring in Mole National Park in Ghana, Burton (2012) found that patrol observations underrepresented the park's mammal species diversity, and resulted in different inferences about spatial patterns in mammal abundance, compared to camera trap surveys. Observer error such as the mis-categorisation of a natural mortality carcass as an illegal hunting mortality, or errors in the recoding of GPS locations, may also compromise monitoring accuracy.

Furthermore, the rangers who collect data and the park managers who make use of these data, do not operate like predictable algorithms. They are people with skills, values, and priorities that inevitably influence monitoring and management success. This human dimension is particularly important in the context of ranger-based monitoring, where those responsible for collecting and using data are not professional ecologists. These individuals must fit monitoring in alongside more immediate management and protection duties. Also, smaller state budgets and fewer skilled professionals translate into far less monitoring of natural resources in developing compared to developed countries (Danielsen et al., 2009).

## 1.2. Problem statement and research gap

To be effective, biodiversity monitoring programmes must (a) reliably detect changes in variables of interest (e.g. animal population abundance or harvest levels ), and (b) produce results that are adequately integrated into conservation management decisions (McDonald-Madden et al., 2010). Millions of limited conservation dollars are spent on monitoring that has no reasonable chance of detecting change (Field et al., 2007). An important contribution research can make, therefore, is to quantitatively evaluate the accuracy and precision of trend detection for different monitoring designs. Indeed, much previous research has focussed on evaluating the sampling rigour of monitoring schemes (Field et al., 2005; Jones et al., 2017). Ranger-based monitoring, however, presents a unique challenge in that data are not collected according to a systematic sampling design. Patrols are not explicitly monitoring-focussed and are subject to biases such as changes in patrol effort through space and time (Keane et al., 2011). Evaluating the rigour of ranger-based monitoring is thus difficult and few examples of such evaluations exist in the literature (Burton, 2012; Jachmann, 2008).

Compared to quantitative evaluations, little research has considered the important socio-economic and political dimensions of conservation monitoring, particularly by non-scientists (Earle, 2016). A well-financed monitoring scheme with a robust survey design may nevertheless fail to contribute to conservation outcomes if there is no clear framework for using the results to inform management decisions. Conservation monitoring programmes are often conceived as ends in themselves; but in order to be effective, they must be explicitly embedded within and inform a broader framework of conservation science or management (Nichols and Williams, 2006). Adaptive management of biodiversity (whereby ongoing monitoring helps evaluate and improve management interventions with uncertain outcomes) is a technically well-developed and commonly promoted conservation tool, yet practical examples of its application remain sparse (Keith et al., 2011). Implementation of adaptive management requires substantial human and financial resources over and above those required for baseline monitoring, as well as time for testing and evaluating management actions (McDonald-Madden et al., 2010). There is a need to better understand the reasons why adaptive management so often fails to be implemented in practice (Allen and Gunderson, 2011), and is instead replaced by trial-and-error management, based on expert judgement.

Finally, previous sociological research with rangers has demonstrated the power of engaging ranger perspectives and ideas to better understand and address conservation challenges (Moreto et al., 2017; Moreto and Lemieux, 2015). Yet, much of this work has come from a criminology and policing perspective, with rangers conceived of as law enforcement officers with roles similar to those of policeman (Moreto and Matusiak, 2017). While this has produced much valuable insight, rangers' responsibilities extend beyond law enforcement, with biological monitoring being a major additional role in many protected areas globally (Belecky et al., 2019). Furthermore, as far as I am aware, no previous work has sought to understand how rangers themselves perceive and engage with patrol-based data collection, and the broader management uses of these data. This is important because poor engagement with, and ownership of, monitoring by those undertaking it may compromise data quality and thereby limit evidence-based conservation.

## 1.3. Research aims and questions

Using the monitoring of elephant poaching in the Zambezi Valley, Zimbabwe, as a case study, this DPhil research aims to investigate (a) the reliability of ranger-based monitoring data and,

(b) the extent to which it is effectively used to inform conservation management. I pose the following research questions:

1. What factors affect the reliability of ranger-collected data on elephant poaching, and how can inference from such data be made more reliable?
2. What factors affect the active and meaningful engagement of rangers with monitoring?
3. What factors affect the extent to which park managers use ranger-collected data to inform their decisions?
4. How can the insights from questions 1-3 be used to maximise the contribution of ranger-based monitoring to effective protected area management?

I use the term *reliability* to refer to the accuracy (or bias) and precision (level of uncertainty) with which ranger-collected data capture true underlying patterns in poaching (Nuno et al., 2013). The specifics of how reliability is defined will vary depending on whether the focus is spatial or temporal patterns in poaching (see Chapter 4). I use *active and meaningful engagement* to refer both to rangers themselves seeing data collection as important, and to supervisors of monitoring programmes seeing rangers as active agents whose ideas and motivations are considered and engaged. This kind of active and meaningful and active engagement will have implications for the quality and consistence of the data that rangers collect (see Chapter 5).

## 1.4. Conceptual framework for Thesis

The object of this study is the ranger-based monitoring and management cycle (Fig. 1.1). Managers implement actions (e.g., new patrol strategies) based on an evaluation of the data reported from ranger patrols (e.g., location of illegal activities). Data reliability and use are affected both by the technicalities of data collection and analysis (data dynamics), as well as the values and perceptions of the rangers who collect these data and the park managers who use it (human dynamics). This Thesis combines quantitative methods (to understand observation uncertainties in this system), and qualitative methods (to interrogate implementation uncertainties) to address the overall research questions. The intention is that the quantitative analysis of data dynamics and the qualitative analysis of human dynamics will provide complementary insights (Fig. 1.1). For example, the capacity and resources within the implementation environment (qualitatively analysed) may affect levels of ranger patrol effort and thus data reliability. In turn, the statistical power of monitoring to accurately detect change (quantitatively analysed) will determine its usefulness for guiding management.

The cycle in Figure 1.1. is embedded within a broader socio-ecological system (SES). Following the influential framework developed by Ostrom (2009), the focal elements of my case study SES are the broader resource system (the Mana-Chewore protected landscape), resource units (elephants), resource users (poachers), and a governance system (rangers and park managers). Addressing the above research questions will involve understanding and measuring the outcomes of interactions between these elements (Ostrom, 2009).

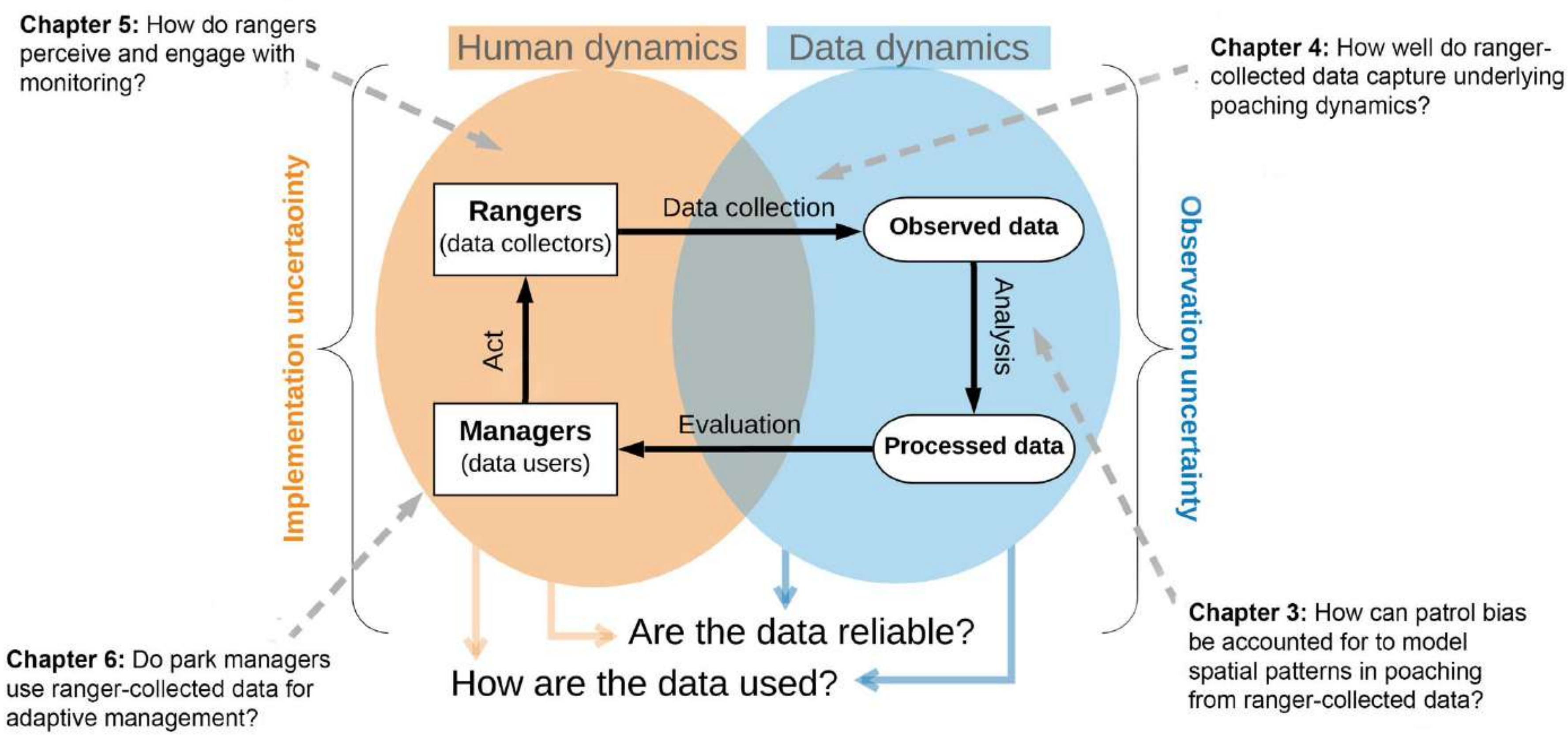



**Figure 1.1.** Conceptual framework for this DPhil research, showing the ranger-based monitoring-management cycle (centre), the two research foci (human dynamics and data dynamics), and the primary research questions (bottom). How each of my four data Chapters fit into this framework, and the focus of each Chapter, is also shown.

## 1.5. Thesis overview

In **Chapter 2**, I introduce the global programme for monitoring the illegal killing of elephants (MIKE), the case study of ranger-based monitoring that I used for this research. I also describe my case study site in Zimbabwe, the Mana-Chewore World Heritage Site in the Zambezi Valley. Finally, I provide a higher-level overview of the quantitative and qualitative methods used in this Thesis.

*Part 1: Data dynamics and observation uncertainty*

In **Chapter 3**, I present the results of spatial models of elephant poaching in Mana-Chewore. Models were based on detections of carcasses by ranger patrols (201 carcasses, 2000–2017) and used statistical methods to correct for patrol bias. I followed a participatory modelling framework, using interviews with rangers and managers to help build and evaluate these models. I found that poaching patterns in the bias-corrected scenarios differed among themselves and from the uncorrected scenario. Practitioners interrogated the credibility of the predictions in each scenario and thus helped discern true poaching patterns from those explained by patrol bias. Proximity to water was the strongest driver of poaching, probably reflecting both poacher and elephant behaviour. These results demonstrate the value of combining multiple lines of evidence (statistical models and interview responses) for more robust inference in the face of uncertainty. This analysis lays the ground for identifying possible sources of bias in ranger-collected data (investigated further in Chapter 4) and provides an example of how analysing patterns in real data might inform local anti-poaching and elephant management (investigated further in Chapter 6).

This Chapter was published in May 2020 in the journal *Biological Conservation*: Kuiper, T., Kavhu, B., Ngwenya, N.A., Mandisodza-Chikerema, R., Milner-Gulland, E.J., 2020. Rangers and modellers collaborate to build and evaluate spatial models of African elephant poaching. Biol. Conserv. 243, 10843 (see the note on co-authorship on page 8 for author contributions).

In **Chapter 4**, I present results from the mathematical simulation models I developed to quantify how various characteristics of ranger patrols (such as patrol effort and spatial coverage) interact with poaching dynamics to affect the power of ranger-collected data to detect underlying spatial and temporal trends in poaching. I parameterised these simulations using empirical poaching data and analysis from Chapter 3, as well as insights from the interviews conducted for Chapters 5 and 6. Results showed that under current conditions at my study site (intermediate patrol effort that is often spatially constrained), ranger-collected data are unlikely to have strong quantitative power to detect trends in poaching. However, this did depend on aspects of patrol performance that can be manipulated by managers, however. Importantly, the relative trend-detection performance of different patrol strategies depended in large part on the particular management question (the magnitude of change in poaching that managers wish to detect reliably, for example). These results, therefore, complement my findings on the various ways managers use ranger-collected data in Mana-Chewore (Chapter 6).

*Part 2: Human dynamics and implementation uncertainty*

In **Chapter 5**, I present results from interviews with 23 rangers at my study site which assessed the importance that rangers ascribed to data collection within their broader occupation, and their level of engagement with data management and use. I found that rangers saw the collection of biodiversity data as a routine duty that helped guide patrol strategy. Reporting these data was perceived as a primary way of demonstrating fulfilled responsibilities to their supervisors. Rangers did not, however, engage actively with data management and use. Ranger sentiment was evenly divided between those who said feedback on how the data they collected were used would motivate more engaged data collection, and those who said they would continue collecting data regardless, out of duty. Three elements of the occupational culture of rangers at my site—a strong sense of duty, deference to authority and knowing their defined responsibilities within the organizational hierarchy—were identified as key drivers of their engagement with monitoring. Building on these findings, I developed a theory of change to support more meaningful engagement of rangers with monitoring. Such engagement could boost data volume and reliability (Chapter 4), thereby creating more evidence on which to base conservation management decisions (Chapter 6).

This Chapter was published in September 2020 in the journal *People and Nature*: Kuiper, T., Massé, F., Ngwenya, N.A., Kavhu, B., Mandisodza-Chikerema, R.L., Milner-Gulland, E.J., 2020b. Ranger perceptions of, and engagement with, monitoring of elephant poaching. People Nat. pan3.10154 (see the note on co-authorship on page 8 for author contributions).

In **Chapter 6**, I present results from interviews with park managers in Mana-Chewore, which sought to understand the extent to which managers use ranger-collected data on elephant poaching to inform their anti-poaching strategies. I specifically sought to understand manager perspectives on, and their extent of adoption of, adaptive management (which I defined in this Chapter as the analysis of trends in poaching data to improve anti-poaching strategies). I interviewed 8 park managers, as well as 17 national-level informants (mostly staff of the government wildlife department) familiar with local elephant management practices. I found that park managers valued ranger-collected elephant poaching data and used them to guide patrols. Managers did not, however, systematically analyse trends in poaching data, nor did they adjust their anti-poaching strategies in response to these trends. A major reason for this is that managers felt that the costs of adopting such an adaptive management approach outweigh the benefits. Specifically, managers were unfamiliar with the technicalities of data analysis and felt that management based on intuition, experience and more reactive data-use was more familiar and dependable. As a result, there was a low level of ownership of data-based adaptive management among managers. Furthermore, the perspectives, priorities, and needs of park managers have not been adequately considered in the external programmes that are seeking to promote adaptive management in Mana-Chewore. Looking ahead, I developed a theory of change that outlines key priorities and actions to promote effective use of ranger-collected data to inform anti-poaching strategies in Mana-Chewore. This theory-of-change drew on technology adoption theory, and the concept of human-centred design, to ensure that solutions take as their starting point the perspectives, concerns, priorities, and decision-making context of park managers.

*Synthesis*

In **Chapter 7**, I present a summary and discussion of what I see as the contributions of this DPhil research to the field of conservation science and socio-ecological systems research. I identify five key higher-level insights, or themes, that cut across two or more of the data Chapters outlined above. For each theme, I review previous work, summarise the insights from my research, and suggest avenues for future research.

# Chapter 2: Case Study and Methods

In this chapter I provide an overview of the broader ranger-based monitoring programme which I use as a case study for this research (section 2.1), my particular study site in Zimbabwe (section 2.2), and the qualitative and quantitative methods I used to address my research questions (section 2.3).

## 2.1. The MIKE programme: ranger-based monitoring of elephant poaching

*Elephant poaching and the global ivory trade*

The poaching of elephants for their ivory is a prominent example of the global illegal wildlife trade (Hauenstein et al., 2019). Wittemyer et al. (2014) estimated that over 100 000 African elephants were illegally killed for their ivory during a peak in continental poaching from 2010 to 2012. This has had substantial consequences for source country economies (Naidoo et al., 2016), socio-political stability (Douglas and Alie, 2014), and wider ecological systems (Malhi et al., 2016). The monitoring and management of this poaching threat provides a model case study of the observation and implementation uncertainties outlined in Chapter 1. It also provides a comprehensive case study of the importance of ranger-based monitoring for conservation outcomes.

The elephant poaching policy space may be conceptualised as a set of complex global to local socio-ecological systems, each with elephant population trends and ecology in one dimension and the diversity of human actors involved in their exploitation and conservation in another (e.g., local communities, government, NGOs, criminal syndicates, and scientists). At the global scale, this might include continental trends in elephant populations and poaching rates (Wittemyer et al., 2014), transnational ivory trade networks (Underwood et al., 2013), inter-governmental decision making about trade (Stiles, 2004), and markets in consumer states (Zhou et al., 2018). A local-scale supply-side socio-ecological system (i.e. single protected area) might involve adjacent rural communities, illegal harvest gangs directed by a regional syndicate, government anti-poaching patrols, and local NGOs (Harrison et al., 2015). A significant challenge is that there remains significant uncertainty about many aspects of these socio-ecological systems at different spatial scales.

*International policy on elephant poaching*

Accurate estimates of rates of elephant poaching at different scales, and how they change over time, are critical for understanding drivers of poaching (Hauenstein et al., 2019), and evaluations of the effectiveness of conservation policies designed to reduce poaching. These may be global interventions like legalisation of international trade (Biggs et al., 2017), domestic ivory bans like that recently declared for China (Harvey et al., 2017), or local supply-side interventions such as intensifying law-enforcement patrols to deter illegal harvesters (Hilborn et al., 2006).

Ivory policy has dominated international wildlife trade discourse, particularly since the establishment of the Convention on the International Trade in endangered Species (CITES) in 1973. CITES is an international conservation agreement among governments (there are a total of 183 parties to the convention) that develops regulations to ensure that international trade in wild plants and animals does not threaten their survival. The 1989 CITES ban on international trade in ivory was a landmark occasion for CITES and for international conservation policy in general, fuelling much debate around the efficacy of bans, a matter that is still moot today (Biggs et al., 2017). It became clear that the evidence base for making decisions about ivory was scant. Stiles (2004) remarks, for example, that there is simply no adequate data pre- and post- 1989 to test the effects of the ban on elephant poaching levels. In recognition of the need for baseline data on elephant poaching, CITES established the MIKE programme (Monitoring of the Illegal Killing of Elephants) at the 10$^{th}$ conference of the parties to CITES in Harare, Zimbabwe, in 1997. A complementary programme, the Elephant Trade Information System (ETIS), also established at this time, focuses on measuring levels and trends in ivory trade by recording seizures of raw and worked ivory along trade chains (Milliken et al., 2016).

The primary source of MIKE elephant poaching data are elephant carcasses encountered by wildlife rangers while on patrol, with ranger-based monitoring currently operating at over 80 MIKE sites in Africa and Asia (CITES Secretariat, 2019). There are currently 63 MIKE sites across 30 African countries and the database currently stores over 19 00 carcass records for the continent[2] (Fig. 2.1). Poaching trends from multiple MIKE sites are aggregated to the sub-regional and continental levels using the PIKE (Proportion of Illegally Killed Elephants) index:

[2] Data are available online at https://cites.org/eng/prog/mike/index.php/portal#Access%20to%20MIKE%20Data

the number of poached carcasses detected per site per year, as a proportion of all carcasses detected (including natural mortalities). PIKE data for four African subregions between 2003 and 2018 are shown in Figure 2.1. PIKE data are summarised by the MIKE Technical Advisory Group and presented at key international wildlife trade policy gatherings, such as the triennial Conference of the Parties to CITES, where key decisions about ivory trade and anti-poaching policy are made by representatives of the signatory governments (IUCN et al., 2017).

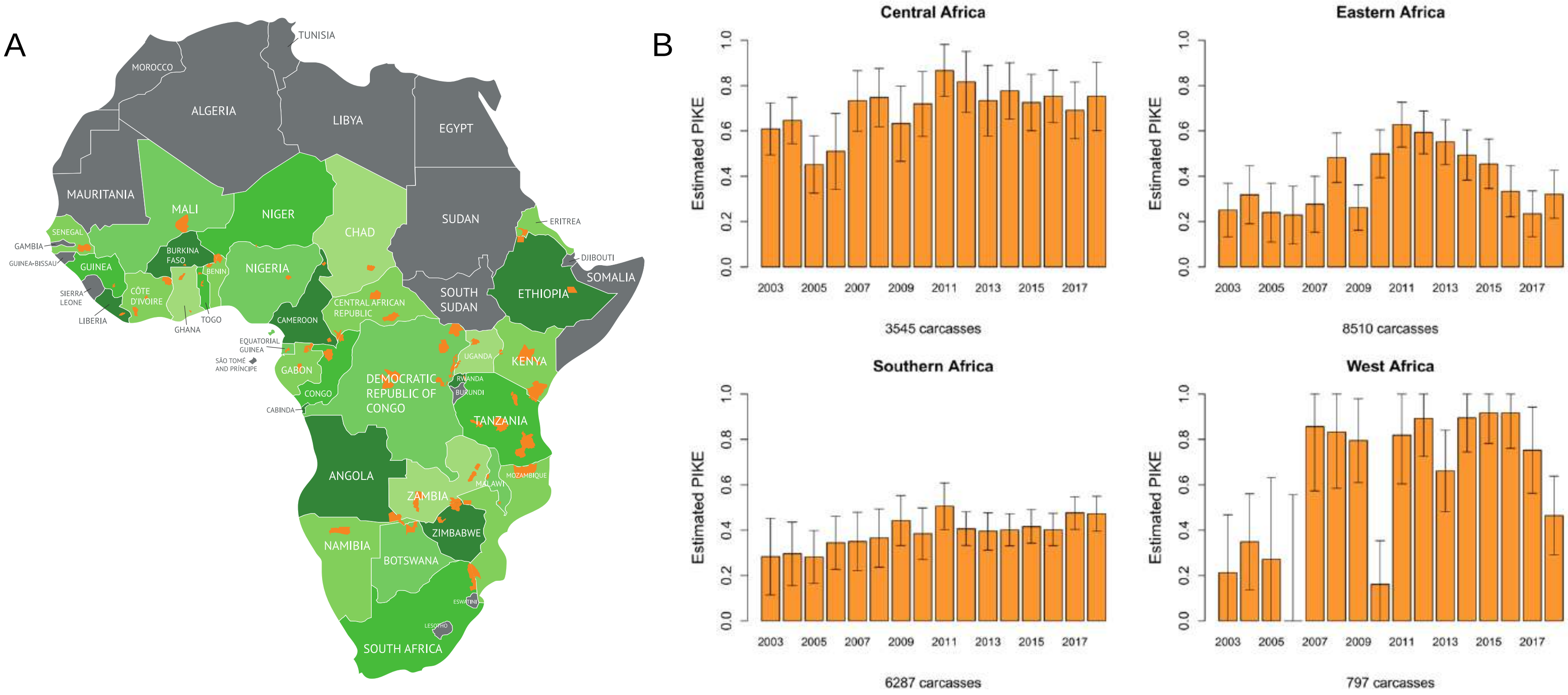



Figure 2.1. (A) The 63 current Monitoring of the Illegal Killing of Elephants (MIKE) sites (indicated in orange) across 30 African countries[3]. (B) Trends in estimated elephant poaching (measured as PIKE, the proportion of all detected carcasses that were illegally killed) across four African sub-regions. Graphs are copied from CITES Secretariat (2019) and are based on 19,139 carcasses detected, mostly by rangers, across 27 countries ). Values represent marginal means with 90% confidence intervals. PIKE values greater than an estimated 0.54 indicate potentially unsustainable levels of harvest (Wittemyer et al., 2014).

[3] This map was accessed on 10 September 2020 from https://cites.org/eng/prog/mike/index.php/portal. Shades of green are simply to distinguish country boundaries.

PIKE data are also used to identify factors associated with higher poaching levels, such as poor governance quality at the national level, poverty at the local level, and the demand for ivory at the global level (Hauenstein et al., 2019). There are significant causes for concern, however, about the reliability of the PIKE index in terms of accurately capturing true poaching rates. An advantage of PIKE is that it is, at least partially, independent of the ranger patrol effort invested in carcass detection as both the numerator and denominator are affected by effort (Burn et al., 2011). However, a major disadvantage is that PIKE fluctuates with natural mortality independently of the poaching rate, and it assumes equal detectability of poached and natural mortalities. In reality, poached carcasses are likely to be significantly easier to detect due to cues like gunshots and poachers' spoor, and long-term patrol bias towards poaching hotspots (see Chapter 4). PIKE may be subject to numerous other biases such the stochastic effects of small carcass sample sizes (Wittemyer et al., 2014).

*The goals of the MIKE programme: global and local*

The MIKE programme represents a prime example of evidence-based decision-making: "*The overall aim of MIKE is to provide information needed for elephant range States and the Parties to CITES to make appropriate management and enforcement decisions*" (CITES Secretariat, 2017). A comprehensive review of MIKE during the period 2006-2012 (Malpas and D´Udine, 2013) divided these objectives into two key components:

1. The *international policy aim*: to inform CITES-level decisions on ivory trade.
2. The *range state management aim*: to strengthen capacity to use MIKE data for local elephant management and law enforcement.

Perhaps the most significant challenge for MIKE to date has been the tension between achieving these two aims. Malpas and D´Udine (2013) conclude that MIKE had contributed well to international CITES policy but had largely failed to address the local management needs of elephant range states. A new five year (2014-2018) programme, MIKES (Minimizing the Illegal Killing of Elephants and other Endangered Species)[4], was developed partly to address this limitation by including investment in both baseline monitoring and local law enforcement at eight focal African MIKE sites (CITES Secretariat, 2016).

[4] https://cites.org/eng/prog/mike/proj/mikes [Accessed 25 April 2018]

## 2.2. Case study site: The Mana-Chewore World Heritage Site

An important decision I needed to make at the beginning of my research was whether to pursue a 'narrow and deep' approach in which I would investigate a single case study in-depth, or a 'broad and shallow' approach in which I collected data from several case study sites for a shorter period at each site. The latter approach would be achieved by visiting several designated MIKE sites at which rangers collected data on elephant poaching and would have the advantage of greater generalisability of my findings. In the end, however, I decided that an adequate understanding of the factors affecting the reliability and use of ranger collected data (my main research questions) would require in-depth investigation through several phases of field work at the same site. A single-site focus also allowed me to conduct extensive quantitative and qualitative work at the same site, thus allowing truly interdisciplinary work where these different methods informed each other. Partly because I am myself Zimbabwean and have research and practical conservation experience there, I chose as my study site the Mana-Chewore World Heritage Site in northern Zimbabwe.

This site comprises three adjacent protected areas (PAs): Mana Pools National Park and the Chewore and Sapi Safari Areas (Fig. 2.2). These three PAs together form the Zambezi Valley MIKE site and cover an area of 6 678 $km^2$ (Fig. 2.2). The region is designated as a World Heritage Site under the United Nations Scientific and Cultural Organisation (UNESCO), and also forms part of a wider 'Man and the Biosphere Reserve', another UNESCO designation. Several private ecotourism 'safari' camps exist in the Mana Pools National Park and the Sapi Safari Area (mainly along the Zambezi river). The Chewore Safari area is managed primarily for trophy hunting, with several private firms leasing land and operating camps in the area. The wet season is relatively short (November to March), with a longer dry season (April to October), mean annual rainfall of 650-750mm, and a mean annual temperature of 29$^{o}$C. Vegetation is a mosaic of mopane woodland (*Colophospermum mopane*), miombo woodland (*Brachystegia* and *Julbernardia* spp.), open savannah, and *Setaria* grassland (Matawa et al., 2012). The perennial Zambezi river in the north is the main water source, with several seasonal rivers and pans further inland (Fig. 2.2).

The Zambezi Valley elephant population (spread across these three PAs and an additional 8000 $km^2$ of adjacent protected land) was estimated at 11 656 in 2014 (Dunham, 2015), down 42% from an estimated 19 981 in 2003 (Dunham, 2004). The primary cause of decline was poaching

(ZPWMA, 2015). This large elephant population and high poaching rate means that it is one of only 12 MIKE sites with large enough annual carcass sample sizes for robust inference (Wittemyer et al., 2014). Furthermore, the site is one of only eight focal sites at which the new MIKES programme is being implemented (see above) and should therefore illustrate a 'best-case' example of the integration of elephant mortality data into local management.

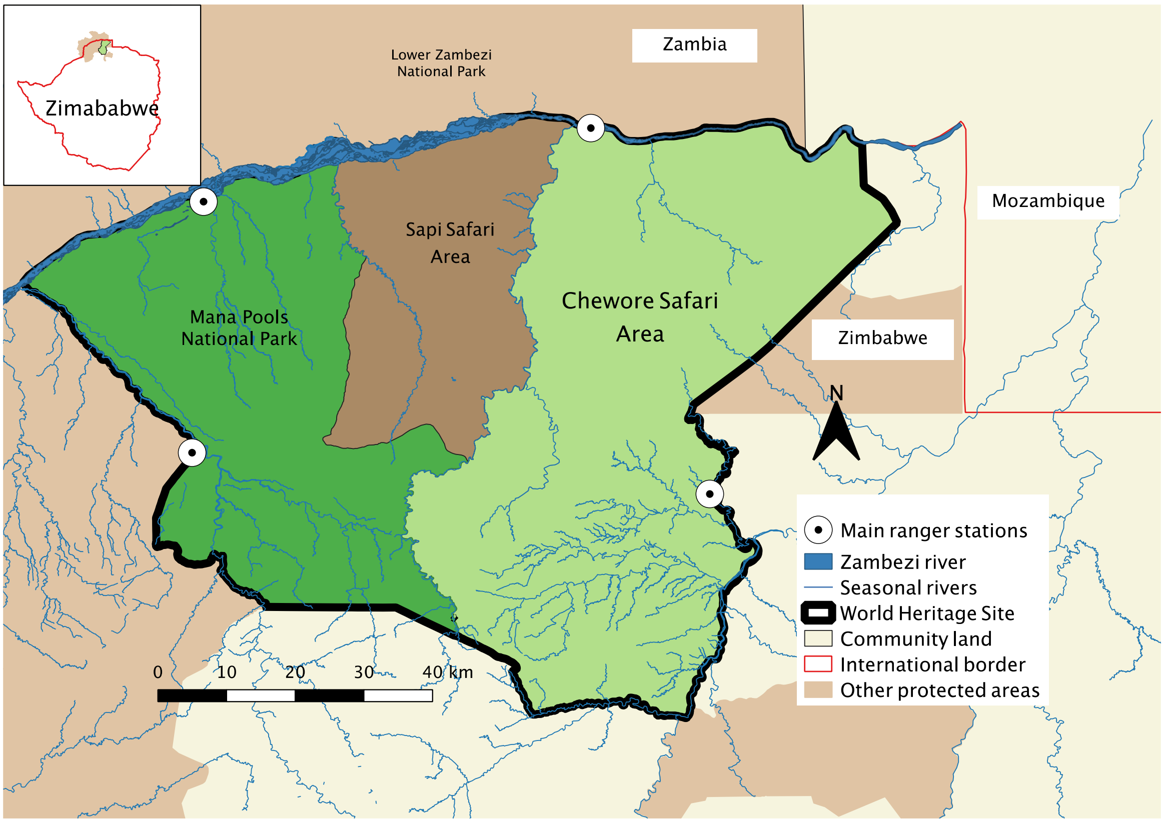



**Figure 2.2.** My field site in northern Zimbabwe: The World Heritage Site encompassing three protected areas. The four ranger bases at which I conducted field work are also shown.

The Mana-Chewore site is managed by the Zimbabwe Parks and Wildlife Management Authority (ZPWMA or simply Zim Parks). Around 140 rangers work at the site, based at four main ranger stations, which are the management centres for the different regions of Mana-Chewore (Fig. 2.2). At each station, an individual in the position of 'area manager' is responsible for overseeing management, together with 2-4 additional staff responsible for ranger supervision and several sub-areas of management. Primary manager responsibilities include ranger supervision, law enforcement, and the management of resources (vehicles, fuel, patrol equipment, etc.). The primary responsibility of rangers is to conduct field patrols, which last several days and focus on monitoring and deterring illegal activities. Chapter 5 provides an extensive overview of ranger patrols in Mana-Chewore, the various forms of data that rangers collect on patrol and how elephant poaching data are recorded and reported. Chapter 6 provides a similar overview of the various ways that park managers use ranger-collected data on elephant poaching.

*Field work and in-country collaborations*

I conducted an initial scoping trip to Zimbabwe in January 2018 to develop collaborations and apply for research permission. Two extensive data collection trips were then conducted: the first from July to September 2018 and the second from July to August 2019. During these trips, I spent several weeks living alongside rangers at each of the four main ranger stations in Mana-Chewore (Fig. 2.2). At two of the stations, I lived in unused ranger accommodation (a small house within a broader complex), and at the two remaining stations I camped in a tent near the rangers' houses. This afforded me the opportunity for many informal interactions with rangers and management staff, helping me to build rapport as well as providing candid insights not possible during the formal interviews I conducted. Several photographs taken during fieldwork in Mana-Chewore in 2018 and 2019 are shown in Figure 2.3 below.

I registered this research project with the Research Council of Zimbabwe in 2018 (certificate no. 03211), and secured research authorization from the Zimbabwe Parks and Wildlife Management Authority (Permit no: 23(1)(C) 43/2018). My research forms part of a new collaboration with the Chinhoyi University of Technology (CUT) in northern Zimbabwe, with Prof. Victor Muposhi and Prof. Edson Gandiwa of CUT visiting Oxford in July and October 2018, respectively. Furthermore, the research has been guided and supported by the directors of two local conservation NGOs, the Zambezi Society and the Tashinga Initiative.

**Figure 2.3**. Several photographs from fieldwork trips to Mana-Chewore (used with permission).

## 2.3. Methods overview

Conservation scientists are increasingly embracing robust techniques to deal with the observation and implementation uncertainties that I identified in Chapter 1, which I described as particularly important in the context of ranger-based monitoring. A better understanding of these uncertainties will help ranger-collected data contribute more effectively to biodiversity conservation outcomes. Below, I provide a broad overview of the quantitative and qualitative methods I have use to better understand these uncertainties and address my main research questions.

*Quantitative tools for understanding and addressing observation uncertainties*

The mathematical and statistical approaches discussed below offer significant promise in understanding and accounting for bias and uncertainty in ranger-collected data, thus increasing the usefulness of these data for biodiversity management. In Chapter 4, I used the virtual ecologist approach (described below) to understand the factors affecting the power of ranger patrols to detect changes in elephant poaching. In Chapter 3, I used statistical modelling approaches to account for ranger patrol bias when inferring spatial patterns in poaching from ranger-collected data.

*The virtual ecologist framework: mathematical simulations to understand data bias*

It is essential to understand potential bias in the monitoring process before making inferences about underlying system processes (Nuno et al., 2015). An obvious challenge is that the true system properties are often not known (e.g., the true number and distribution of poached elephant carcasses), and so there is no reference against which to assess the reliability of monitoring data. One approach is to validate simple cost-efficient monitoring protocols through comparison with the results of more robust surveys of the same study system (Houser et al., 2009). However, such data are costly to collect and even when available they are, to a lesser or greater degree, partial representations of the truth (Fulton et al., 2005). A promising complement to obtaining robust and independent empirical data on the true system state is to simulate a virtual version of the ‘truth’. This ‘virtual ecologist’ approach involves generating virtual data by simulating both ecological processes (e.g. the true number and distribution of individuals in a population), and the observation process used to collect data on these processes (Zurell et al., 2010). The goal of this approach is to better understand the likely effects of different realistic scenarios or strategies of monitoring (e.g., low or high patrol effort in the case of ranger-based monitoring) on the reliability of monitoring data (i.e., how closely these data represent the "true" state of the system). By overlaying the monitoring process onto the simulated reality in a hierarchical way, virtually observed data can be evaluated against the ‘true’ properties of the system (which the researcher has full access to through simulation). The strength of this approach is that it allows the performance of sampling methods to be rigorously tested against a known truth, and it has come to be used widely for evaluating and optimising monitoring protocols (Ficetola et al., 2017; Shannon et al., 2014; Thanopoulou et al., 2018). The approach both acknowledges and seeks to measure the effects of observation error when inferring patterns and process from observational data (Grimm, 1999).

Two sub-models are typically constructed; a resource operating model to simulate the underlying socio-ecological system being observed, and an observation or monitoring model to simulate the process by which data on the system are gathered (Fig. 2.4). I will illustrate the approach using an example from the literature. Nuno et al. (2013) used the virtual ecologist framework to examine the influence of sampling effort and observer biases, as well as simulated population characteristics, on the accuracy and precision of antelope population estimates from aerial surveys in the Serengeti. The effect of ungulate population characteristics (spatial aggregation, average herd sizes, and proportion of juveniles) on survey performance was also tested. They used empirical data on various antelope population characteristics to build a spatially explicit "resource operating model" , a term used in fisheries science (Fulton et al., 2005; Fig. 2.4, step 1). This model was then used to create a simulated set of data on antelope abundance and spatial distribution (Fig. 2.4, step 2). Next, an "observation model" was built to simulate the process of collecting data on this underlying ‘true’ system state. In this case, the simulated process was an aeroplane flying over the Serengeti along transects and (imperfectly) counting antelopes (Fig. 2.4, step 3). Thus an ‘observed’ state was generated (the simulated counts of antelope) for comparison against the underlying ‘true’ state (Fig. 2.4, step 4).

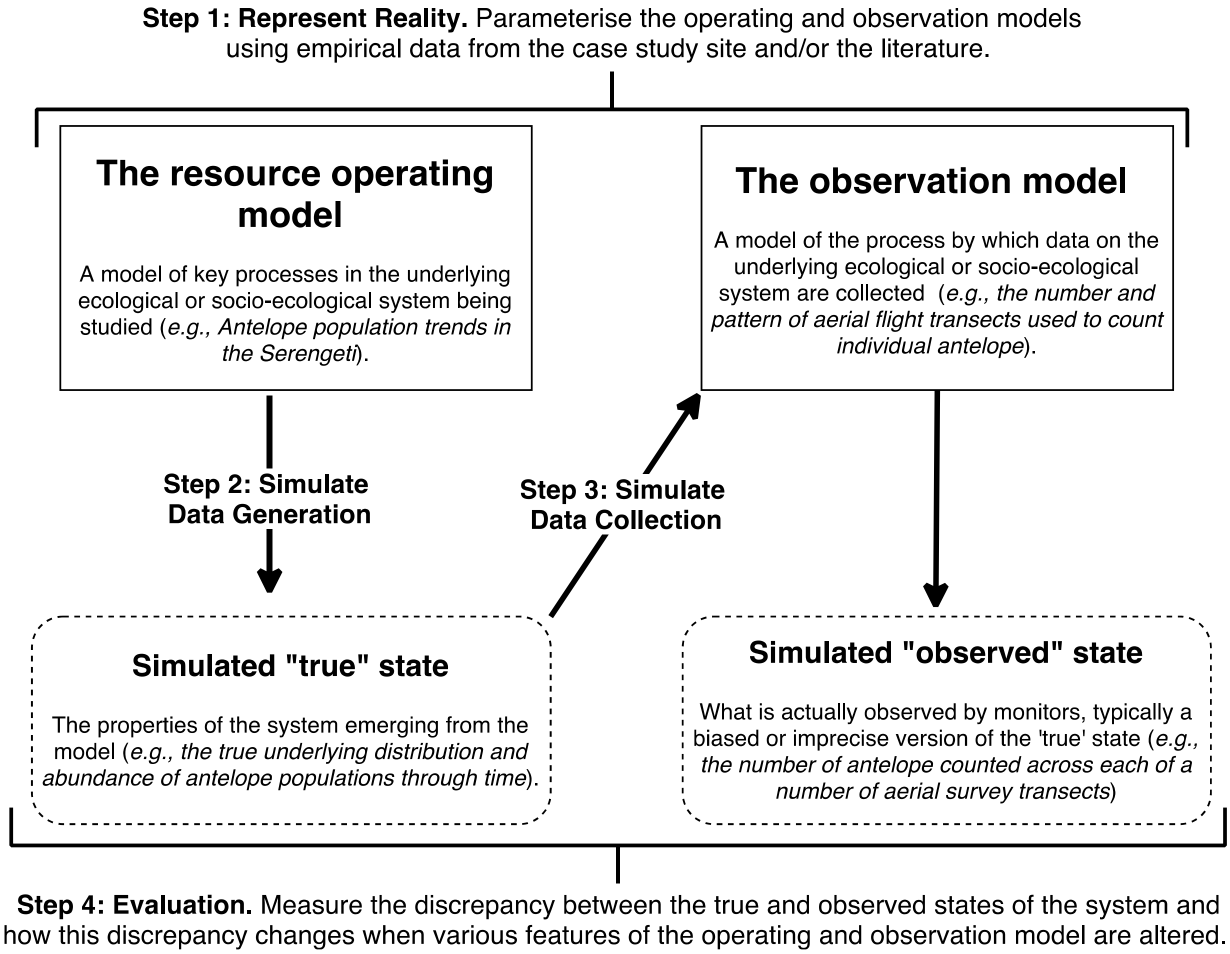



**Figure 2.4.** An illustration of the virtual ecologist framework, using a case study of monitoring antelope populations in the Serengeti. I developed this diagram based on the description of the methods in Nuno et al. (2013).

Nuno et al., (2013) found that survey effort (distance between flight transects) had a large influence on survey precision, but not accuracy. Ungulate population characteristics (spatial aggregation, average herd sizes, and proportion of juveniles) were also shown to have marked effects on survey precision, independently of the observation process. The power of the virtual ecologist approach thus extends beyond evaluating the monitoring process itself, it can also elucidate how underlying processes in the system being observed affect monitoring results. Similarly, Dobson et al. (2019) showed that the magnitude of changes in illegal snaring that occur independently of changes in patrol effort can influence the reliability of catch-per-unit-effort indices for tracking trends in illegal activity based on ranger-collected data.

Since the data collection process is itself modelled, the virtual ecologist technique allows for the experimental variation of key features of this process (e.g., sampling intensity, detectability biases) and interpretation of how each of these affects the performance of monitoring data as a representation of the simulated reality. This has the distinct practical advantage of generating recommendations on which elements of survey design should be prioritised to improve monitoring efficiency, and enabling the implications of different budgetary scenarios on monitoring performance to be evaluated (Kinahan and Bunnefeld, 2012). Rachowicz, Hubbard & Beissinger (2006), for example, used simulations of seabird abundance trends, coupled with simulations of different observation transect layouts and replication intensities, to help select a sampling design that had enough power to detect trends while still remaining logistically feasible. Jones et al., (2017) built spatially explicit simulations of systematic surveys of illegal activities in Gola NP in Sierra Leone. They found that unrealistic levels of survey effort would be required to detect changes in rule-breaking over time; for example, >200 x 1km$^2$ survey cells (30% of the study area) would need to be visited multiple times to detect a 50% decline in hunting activities with reasonable power. This would require an unreasonable amount of resources.

Since the virtual ecologist framework does not depend on independent empirical survey data, it may be more widely applicable as a monitoring validation technique than methods that do require such data. It is important to note that the focus here is less on precisely representing the true state of a particular system, but rather on creating a realistic set of possible true scenarios and then testing whether data collected according to a defined observation process are a robust representation of these scenarios. However, the reliability of conclusions will depend on how well the operating and observation simulation models represent processes occurring in the real world (Fig. 2.4, step 1).

In addition to quantifying bias in the observation process, simulations provide a means for identifying optimal levels of monitoring effort that maximise rigour (e.g., the power to detect trends) while minimising cost. Cost estimates for different sampling protocols enable their relative cost-effectiveness to be assessed (Elphick, 2008). Field et al., (2005) simulated the process of collecting data on declining populations of species of varying prevalence and detectability in a virtual landscape, and then evaluated the power of different survey protocols (number of sites visited and number of repeat visits at each site) to detect these declines. Such evaluations allow managers to identify the resources required to reach an acceptable level of statistical power, thus avoiding both over- and under-investment in monitoring. Importantly, simulations may reveal results that are not intuitive (for example Field et al., 2005 found that common species often require more stringent survey designs), and therefore may lead to recommendations that are unlikely to arise from expert knowledge and intuition alone.

Similarly, Tyre et al. (2003) used simulations of biological surveys to demonstrate the strong effects of false negatives (failure to record a species when it is actually present) on the bias and precision of inferences from these surveys. Such an approach allows the researcher to conduct experiments (e.g., how does survey effort affect abundance estimates?) that would be difficult and expensive to carry out in the real world (Milner-Gulland and Shea, 2017).

The virtual ecologist approach has also been applied to data collected by park rangers. Whether or not ranger patrols are effective at deterring poaching activity is important but difficult to measure because data on changes in illegal activity typically come from patrol records themselves (Moore et al., 2018). By using simple mechanistic simulations of ranger deterrence of poachers under different levels of ranger patrol effort, alongside exogenous changes in the prevalence of illegal activities, Dobson et al. (2019) were able to identify robust metrics that are able to identify deterrence from existing patrol data. Keane (2010) similarly used a virtual ranger approach to critically assess the reliability of catch-per-unit-effort (CPUE) indices in detecting trends in illegal activities.

In Chapter 4 of this Thesis, I used the virtual ecologist approach to better understand and quantify the factors that influence the reliability of ranger-collected data (i.e., how close the data capture true poaching trends).

*Statistical methods for robust inference from messy data*

While mathematical simulations can help us understand the underlying processes producing bias in observational datasets like ranger patrol records, statistical models can help account for these biases during the analysis stage. The first step is to understand the process by which data are collected, and the various potential ways that bias might be introduced (Dobson et al., 2020; Fig. 2.5A). For example, observers (such as rangers on patrol) may sample some areas more than others, or sample more intensively at certain times compared to others. Also, certain species or threats might be preferentially recorded over others, or detectability might vary across space and time. Once the observation process is properly characterised, the next step is to develop tools for accounting for the identified biases (Fig. 2.5B). This is the point where statistical models are particularly useful, providing a method for correcting bias and improving the reliability of inferences from messy data (Dobson et al., 2020). In Chapter 3 of this Thesis, I use a simple statistical method for correcting spatial bias in ranger patrols in order to generate more robust maps of the distribution of elephant poaching in my study area (Kuiper et al., 2020).

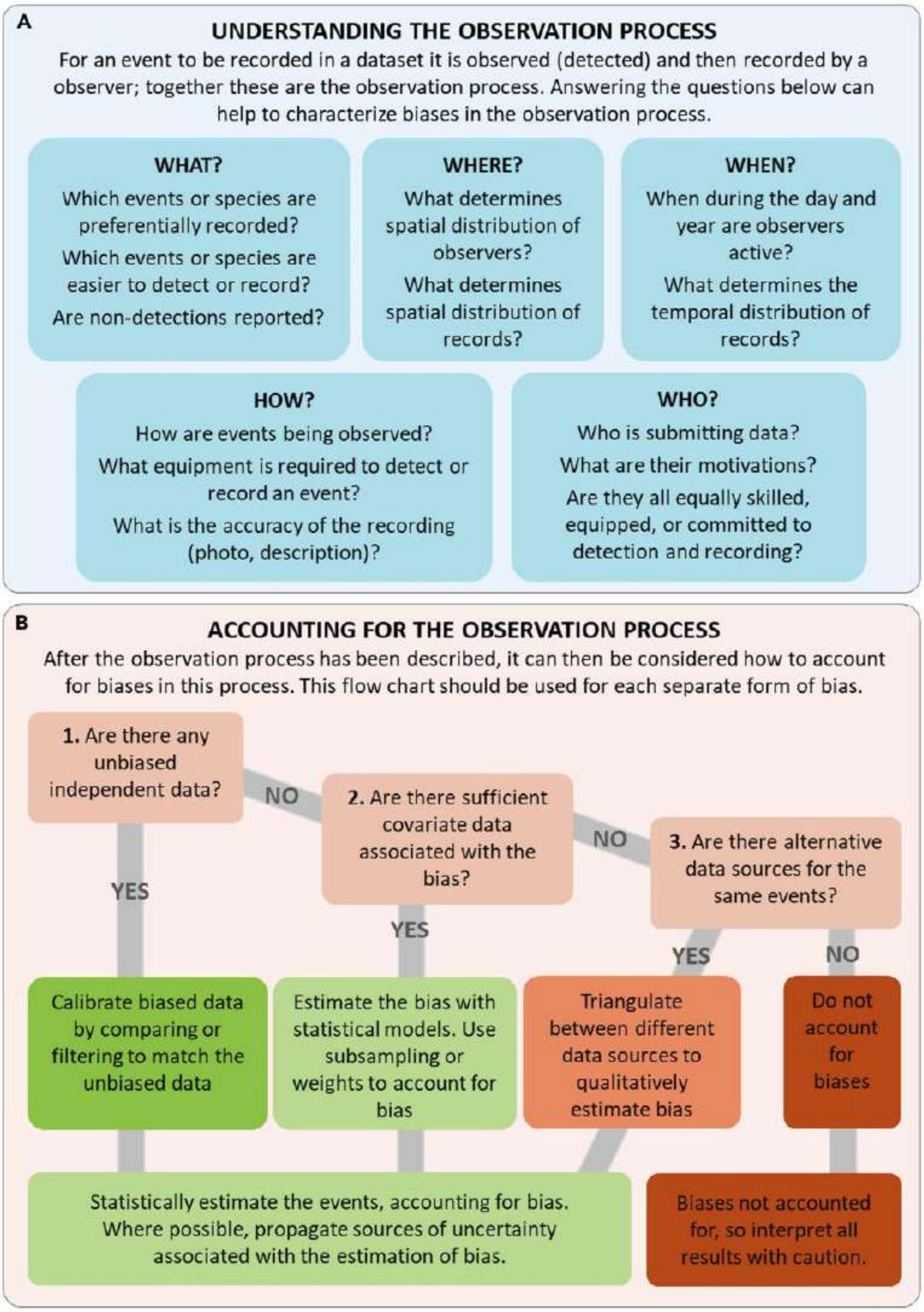



**Figure 2.5.** Understanding and accounting for biases in observational data: (A) Questions to ask in order to better understand the observation process and its biases, and (B) strategies for accounting for these biases. Copied with permission from Figure 3 in Dobson et al. (2020).

As discussed in Chapter 1, uncertainties arise when trying to determine patterns of illegal activity in protected areas from encounters of such activities during ranger patrols (Jachmann, 2008). It can be difficult to determine whether observed changes in illegal activities are due to actual changes in poaching or changes in patrol effort (Moreto et al., 2014). Similarly, high detections of illegal activities in a particular part of a protected area might simply reflect higher patrol effort in that area. It is therefore crucial that true patterns in underlying data are distinguished from those due only to variation in patrol effort across time and space.

Statistical models have been developed to adjust estimated trends in illegal activities by explicitly measuring and accounting for this biased observation process (i.e., uneven patrols). Critchlow et al. (2015), for example, developed estimates of the true distribution of illegal activities (e.g., bushmeat hunting and grazing encroachment) in Queen Elizabeth NP in Uganda by combining an occupancy model of detected illegal activities with a model of survey effort, within a Bayesian hierarchical model framework. The robustness of these results was evidenced in a follow-up analysis in which these bias-adjusted maps of illegal incidents were used to guide ranger patrols, leading to a doubling in detections of similar incidents (Critchlow et al., 2016). Similar reasoning is applied in the use of catch-per-unit effort indices to account for changes in effort through time (see Jachmann, 2008). However, bias in observational data may remain even when using encounter rates per unit effort, because the efficiency of the same amount of patrol effort may vary in different habitats, or at different times (Keane et al., 2011). Therefore O'Kelly et al. (2018b) used novel N-mixture hierarchical models to model both factors affecting snare detectability and those affecting snare abundance, in order to generate more robust poaching estimates.

Bias in the observation process and the methods used to correct it are not unique to ranger patrols. A prominent example of messy observational data (and the advanced statistical methods used to make sense of these data) is citizen science, whereby members of the general public make observations of biodiversity and submit these to scientific databases. This has many parallels with ranger patrol observations in that the observation process is often non-random, may produce false absences and detections, and is vulnerable to spatial correlations in the data (Altwegg and Nichols, 2019). An example is the South African bird atlas project, used to model the distribution of hundreds of species of birds across the country. Altwegg and Nichols (2019) describe the development of specialised occupancy models to strengthen inference from bird observations submitted by the general public, emphasising the need to tailor statistical methods to the structure of the data.

As a final example relevant to the methods I use in Chapter 3, the species occurrence records used to build species distribution models may also be subject to bias in the sampling process, with greater sampling near roads, for example (Gelfand & Shirota, 2019). When these data are combined with randomly sampled background data (as is often the case when building species distribution models), this can lead to over-predicting/fitting of spatial patterns (Brown & Yoder, 2015). In these cases, Barbet-Massin et al. (2012) recommend using geographically-biased sampling of background data to match sampling bias. This is the method I apply in Chapter 3, to account for the constrained geographical extent and variable spatial intensity of ranger patrols in my study area.

In all the case studies considered in this section, different conclusions would have resulted had detectability and observation bias not been considered. These examples illustrate the power of advanced and tailored statistical techniques to enhance the reliability of conclusions drawn from messy data, such as ranger patrol observations. Indeed, such techniques are crucial in this context. Managers may resist changing the pattern of ranger patrols so that they are random and less biased, because the aim of patrols is to focus on certain areas such as poaching hotspots. This is why innovation and improvement are often only possible at the analysis stage, and hence why statistical methods are so important to develop.

In this DPhil, I have sought to integrate the insights from both mechanistic and statistical modelling to help understand and overcome data bias and uncertainty in ranger-observed data.

*Qualitative research: understanding implementation uncertainty*

Although this is rapidly changing  (Bennett et al., 2017), qualitative research is often still seen by conservation biologists as more prone to bias or less rigorous compared to quantitative research (Anderson, 2010). Yet biodiversity conservation challenges inevitably have both social and ecological dimensions, so conservation science requires interdisciplinary approaches. There is increasing recognition of the importance of the human elements of conservation, and hence social science research (Pooley et al., 2014). Furthermore, much of the criticism levelled against qualitative work within conservation biology fails to distinguish between the purposes of qualitative and quantitative methods. Quantitative methods provide a powerful framework for testing specific hypotheses and making focused statistical inferences. Many conservation problems, however, cannot be reduced to experimentally testable hypotheses. In such cases, qualitative methods often provide more appropriate insights (Newing, 2010). The aim of qualitative research is not to 'prove' anything, but rather to provide a narrative account that does justice to the nuances of the study system in relation to the research questions.

In the context of my case study, quantifying the effect of ranger patrol effort on the accuracy and precision of estimated poaching levels using simulation models is one approach to assessing data reliability. Understanding the reasons behind low patrol effort, on the other hand, requires an appreciation of the priorities and constraints faced by managers and rangers. Both approaches are necessary to advance understanding and, crucially, tailor solutions. More broadly, both the reliability and management use of ranger-collected data (the focus of my primary research questions) are influenced by human behaviour. The main qualitative tool I use in this Thesis is the semi-structured interview (although I also used focus groups and participatory modelling in Chapter 3). To help address my research questions, I interviewed a total of 52 respondents in seven stakeholder groups (23 rangers, eight park managers, eight senior staff at the Zimbabwean wildlife authority, three local wildlife consultants, two local Zimbabwean academics, four local NGO leaders, and four higher-level staff of the MIKE programme). Interviews were conducted in English. Although most respondents did not speak English as a first language, all had a good command of the language because English is the standard medium for education in Zimbabwe, and is also used in all documentation (e.g., ranger patrol reports). Interviews were the main method employed in Chapters 5 and 6 and were also used to provide contextual information for Chapters 3 and 4.

*Interviews: a powerful tool to engage stakeholder perspectives*

Qualitative interviews are a powerful and widely used method within conservation science, allowing for in-depth analysis from relatively small sample sizes (Newing, 2010). Interviews typically focus on the experiences of the participants, helping the researcher to understand stakeholder perspectives on what is important and relevant (Young et al., 2018). Given that stakeholders may have significant agency in relation to the research question (e.g., in my case study rangers and managers are directly involved in collecting and using elephant poaching data), such perspectives are crucial. The flexible probing that interviews afford can help construct an accurate account of the institutional and socio-political context of the study, which may also have a strong bearing on the research question. Further, interview responses may also help contextualise quantitative methods by showing which quantitative questions are important and later helping interpret quantitative results (Drury et al., 2011). Nuno et al. (2014) used semi-structured interviews with key stakeholders to investigate the implementation of policies to manage bushmeat hunting in the Serengeti, finding that institutional complexity between and within actor groups hindered effective implementation. Addison, Flander & Cook (2015) were able to demonstrate the limited use of long-term monitoring data to inform decisions within the management of marine protected areas in Australia by interviewing key scientists and managers.

I selected interview informants using targeted sampling of individuals with relevant and intimate knowledge around each of my chapter-specific research questions (Ritchie et al., 2013). In the case of interviews with rangers (Chapter 5) and park managers (Chapter 6), I sought to interview as many individuals as possible at each ranger station, up to a point of 'saturation'. This is the point where the major ideas and patterns in relation to the research question have been identified and any further interviews are unlikely to contribute new information (Ritchie et al., 2013). I used a semi-structured interview structure, meaning that I had a core of key questions and areas for discussion, but conversation was allowed to flow freely in out and out of these discussion areas. This provided a useful balance between focus/comparability (the same basic set of open-ended questions were asked in each interview), and flexibility (I asked different questions as new ideas came up in conversation) (Young et al., 2018).

*Analysing interviews: transcription and thematic analysis*

In each interview, I took notes while simultaneously audio-recording, followed by partial transcription. This process provided a good balance between efficiency and accuracy (Newing, 2010). Halcomb et al. (2006) argue that full verbatim transcription is not always necessary, especially when interviews are more structured and thematic analysis is guided by clear research questions. My analysis sought to address specific research questions, rather than give a complete account of all that was said. It was difficult to justify full transcription of parts of the interview in which participants diverged clearly from topic or provided superfluous detail. Also, each interview included periods where factual information was sought (such as the length of patrols, particular park manager duties, the types of information gathered on patrols) for which only basic summaries were necessary. Finally, I wanted to complete transcription as soon as possible after each interview (I did this mostly on the same day). Partial transcription made this achievable. This was to ensure I captured the 'feel' of the interview and made correct interpretive notes while my memory of the interview was still fresh. In the end I decided that the costs of verbatim transcription outweighed its potential benefits. Furthermore, audio recordings allowed me to check the accuracy of partial transcription and note-taking, where needed.

The interview responses used in Chapters 5 and 6 were analysed using thematic analysis, with the aim of identifying “patterns of meaning” in the interview responses (Braun and Clarke, 2006). The goal was to develop a narrative account of key themes in the responses that spoke to the particular research questions in each chapter. I started with a period of familiarising myself with the interview data as a whole by reading through all the transcripts (immersion). Next, I started making flexible annotations and notes across a handful of transcripts, which slowly developed into a set of initial codes which I then re-applied to the data (Newing, 2010). Both my general research questions, and my specific interview questions, naturally led to a set of pre-defined codes, although new and important themes also developed “bottom-up” from the data (Bernard, 1991). I moved between codes, transcripts and recordings to iteratively refine codes and ensure that they represented the data. The importance of a theme was judged either by its prevalence (repeat occurrence across and within respondents) or by how informatively it spoke to the research questions (Braun and Clarke, 2006). Data were managed and analysed with the help of the software NVivo (QSR International Pty Ltd, 2018). In the results section I use both short quotes and longer quotes in context (Moreto et al., 2017). To avoid the risk of quoting out of context, I was careful to use only those short quotes whose meaning in isolation closely matched their meaning in context (Bernard, 1991).

*Paradigm and epistemology*

The researcher plays an active role in the themes that emerge from qualitative data analysis due to their particular epistemological stance (Braun and Clarke, 2006). Following Lloyd (2018), I am explicit about my epistemological and theoretical stances in three main areas as described below. First, I combined a primarily deductive approach to theme identification, with some indicative elements. On the one hand, I used thematic codes driven by a specific set of clear prior research questions (deductive). On the other hand, wildlife ranger perceptions and experiences are a little-studied field and I wanted to remain open to unexpected themes emerging from the data that were less related to my prior interest as an analyst but that might still have had an important bearing on the research question (inductive). While combining induction and deduction, or theory building and theory testing, in a single study is unusual, it can be useful in some contexts (see Ross & Staw, 1993). Overall, my goal was a detailed account of particular aspects of the data pertinent to the research question (whether these were arrived at deductively or inductively), rather than a rich and broad account of the entire dataset.

Second, I adopted an essentialist epistemology that assumes a straightforward relationship between language, meaning and experience, as opposed to a constructionist perspective which focusses on the underlying socio-cultural context that enables the participants' accounts (Braun and Clarke, 2006). I was interested in the individual motivations, experiences and psychologies of rangers and take what they say more as an accurate reflection of these, and less as a reality constructed by their context. Thirdly, concerning the depth of analysis, I sought first to identify basic and descriptive semantic categories in the data and then interpret their significance in light of the research questions. However, I also sought to identify latent themes (underlying ideologies and systems that drive what the respondents say), leading to a combined approach of semantic and latent pattern identification (Burr, 2006).

*Respondent and researcher bias*

I identified several likely sources of respondent bias which may have affected results. Despite my explanations that I was in no way involved with MIKE or CITES, I occasionally got the sense with some respondents that they felt I was some sort of 'watchdog' seeking to evaluate how well they valued and implemented ranger-based monitoring. Thus, positive sentiment may have been overstated, and problems and challenges understated. Despite these concerns, many other respondents were free in their negative sentiment towards MIKE. I sensed that they perhaps saw the interview as an opportunity to express honest concerns about MIKE in the hope that the dissemination of my research results might improve matters. Triangulation across interviews, informal discussions and document analysis helped identify and minimise inaccuracies and bias in my interpretation of the responses (Newing, 2010). Also, I learned to position myself as a young student with no agenda beyond research and no affiliation with MIKE. Spending informal time with respondents, and returning for a second field trip, also helped minimise this bias. Continued reflection while conducting, transcribing and interpreting interviews revealed a number of my own biases. At times I was guilty of prompting too strongly to elicit an expected response, rather than letting the respondent guide the conversation and give an unforced account. For example, I asked things like "so you don't get much feedback on the data you collect?" or "does it motivate you when you do get feedback?". I did, however, try to keep such prompting to a minimum and use it only when I felt the respondent was too strongly biased in the other direction.

My positionality as the researcher will also have influenced results (Bourke, 2014). I came to this DPhil from a quantitative natural science background and I was learning qualitative approaches for the first time, so my ability to elicit and interpret meaningful information from interviews developed ‘on the job’. Also, I am an ethnically white Zimbabwean, which will have created a certain dynamic given most of my respondents were black and given the racialised history of Zimbabwe. Depending on the respondent, my race may have meant that I was variously viewed with a certain degree of submissiveness (however inappropriate) or subtle contempt (Krauss et al., 1997). The racial difference between my respondents and I may also have led to a certain level of formality and guardedness on the part of respondents. For my part, this racial difference opened up the challenge of accessing and properly understanding the world of the ‘Other’ without mis-representing it (Agyeman, 2008). Finally, I came to this work with great enthusiasm about the potential value of ranger-based monitoring for conservation, and so I may have been biased against results that did not align with this enthusiasm.

*Ethical considerations for this research*

Conducting conservation research that involves people raises a number of ethical considerations that may go beyond established ethical protocols and must therefore be carefully navigated (Brittain et al., 2020). My research involved questions around elephant poaching, which is a criminal activity. I was therefore very aware of the sensitivity of the broader socio-political and legal issues surrounding this research. However, my research focus was not elephant poaching itself, but rather the collection and use of elephant poaching data by rangers and park managers. Nonetheless, there was a small possibility that the ethical issues could have arisen during interviews, concerning information or comments that may indicate certain parties as being complicit in poaching. Before conducting interviews, I had resolved to keep any implicating information confidential and not disclose it to the authorities (Brittain et al., 2020). In order to mitigate this possibility, I held extensive discussions with local stakeholders in Zimbabwe around the sensitivity of the topic during a scoping trip to Zimbabwe in January 2018. I spoke with local NGO leaders, government officials, and local consultants to introduce my research and get their insights. During these exchanges I described the types of research and interview questions I hoped to ask and sought advice about the sensitivity of the topic. I was assured that there was no cause for concern.

Regarding more standard ethical procedures, interview participation was voluntary, and this was made clear to all participants. However, some rangers may have felt pressurised to be interviewed because their peers had been interviewed too, and because their supervisors said that I had been granted permission to conduct interviews. I was also aware that the time participants would need to take to be interviewed may have interfered with their duties at work. I therefore endeavoured to set meeting times that were suitable to the participants and interfered minimally with their work schedules. Prior and informed consent was ensured by giving respondents time to read through a participant information sheet indicating the purpose of the study and how their data would be used. This information was then re-iterated verbally and each respondent given the chance to ask any questions, before signing a written consent form. Interview recordings were stored in an encrypted computer folder and on a cloud server. To protect the personal data of participants, all identifiers within the transcript were anonymised. All qualitative work was approved by the Human Research Ethics Committee at the University of Oxford (CUREC REF: R58336/RE001**).**

# Chapter 3: Rangers and modellers collaborate to build and evaluate spatial models of elephant poaching

## 3.1. Introduction

Monitoring trends within socio-ecological systems (species populations, illegal harvest rates, etc.) is essential for adaptive management, helping managers understand and manage change (Nichols and Williams, 2006). Evaluating anti-poaching strategies, for example, requires reliable measurement of real poaching trends. Data on biodiversity and threats are however difficult to gather at relevant scales, and are often biased and imprecise (Field et al., 2007). Time and resource constraints often mean that monitoring data are collected by people doing other jobs, such as wildlife rangers detecting snares while on patrol or fishers providing records of bycatch species landed. Such opportunistic data present unique challenges to interpretation (Keane et al., 2011). A drop in the detection of poachers' snares, for example, may reflect a shift in patrolling to a 'non-hotspot' area, rather than an actual change in poaching levels.

Another challenge to interpreting observational data is the complexity of the underlying mechanisms generating the data. The behaviours of data generators (e.g. poachers), data collectors (e.g. rangers) and species of concern (e.g. elephants) are likely to interact in complex ways and their relative influence is difficult to disentangle. Dobson et al., (2019), for example, show how deterrence of poachers by rangers can confound inferred trends on the prevalence of illegal activity. Imperfect detectability of illegal activity (like bushmeat snares in thick forest; O'Kelly et al. 2018), and patrol observations that are biased towards certain areas (Critchlow et al. 2015), may similarly confound true patterns.

Participatory modelling is a promising way to design quantitative models that are robust to uncertainty arising from the bias and complexity discussed above (Voinov and Bousquet, 2010). Bringing together people familiar with the system of interest provides essential qualitative context to modelling (Milner-Gulland and Shea, 2017). These may be fishers, wildlife rangers, or protected area managers that have a grounded understanding of how a system works (e.g., where elephant poaching happens) and how data are collected (e.g., what affects ranger movements). Participatory or collaborative modelling involves using the qualitative insights of on-the-ground practitioners and stakeholders in both the design and validation stages of statistical/mathematical modelling (Voinov and Bousquet, 2010). Quantitative models are vulnerable to the data and assumptions used to build them, while qualitative insights are often subjective or incomplete. Combining multiple lines of evidence (statistical outputs and interview responses) is a useful way of addressing this uncertainty. Engaging practitioners in modelling may also create a sense of ownership that amplifies its real-world relevance (Basco-Carrera et al., 2017).

Globally, tens of thousands of park rangers spend significant amounts of time on patrol, encountering plants, animals, and illegal activities. Such data are becoming an increasingly important source of information for both science and conservation (Gray and Kalpers, 2005; Moore et al., 2018). The MIKE programme (Monitoring of the Illegal Killing of Elephants), is a high-profile example of the use of data collected by ranger patrols to inform local and international conservation policy (CITES Secretariat, 2019). MIKE covers 60 sites across Africa, within which >19,000 elephant carcasses have been detected by rangers to date. The data have been used in high profile global and continental analyses (Hauenstein et al., 2019; Wittemyer et al., 2014), but less so at the local site level. In this chapter, I investigate spatial patterns in poached elephant carcasses detected by rangers at a MIKE site in the Zambezi Valley, Zimbabwe. I combine quantitative models with interviews with wildlife rangers and their supervisors to address the following research questions:

(1) What spatial patterns are evident in poached elephant mortalities at the case study site?
(2) How are these patterns influenced by monitoring bias?

## 3.2. Methods

*Study area*

The Chewore Safari Area MIKE site (3390km$^2$; hereafter Chewore) in Zimbabwe is part of the World Heritage Site comprising three adjacent protected areas (PAs): Mana Pools National Park and the Chewore and Sapi Safari Areas (Fig. 3.1). The elephant population in the broader Zambezi Valley declined by an estimated 42% (19,981 to 11,656) between 2003 and 2014, primarily due to poaching (Dunham, 2015; ZPWMA, 2015). Chewore is divided into two management units (north and south) and is also a sport hunting area, with several operators hunting over the dry season (April to October). Elevation varies widely (350-1200m) and the wet season is short (November to March) with average annual rainfall of 730mm (Sibanda et al., 2015). Chewore is dominated by miombo (*Brachystegia julbernardia*) and mopane (*Colophospermum mopane*) woodland. The area is well-drained, and rivers are mostly seasonal, apart from the Zambezi. There are two main ranger stations, and three sub-stations, with a total of 58 rangers as of July 2018 (Fig. 3.1).

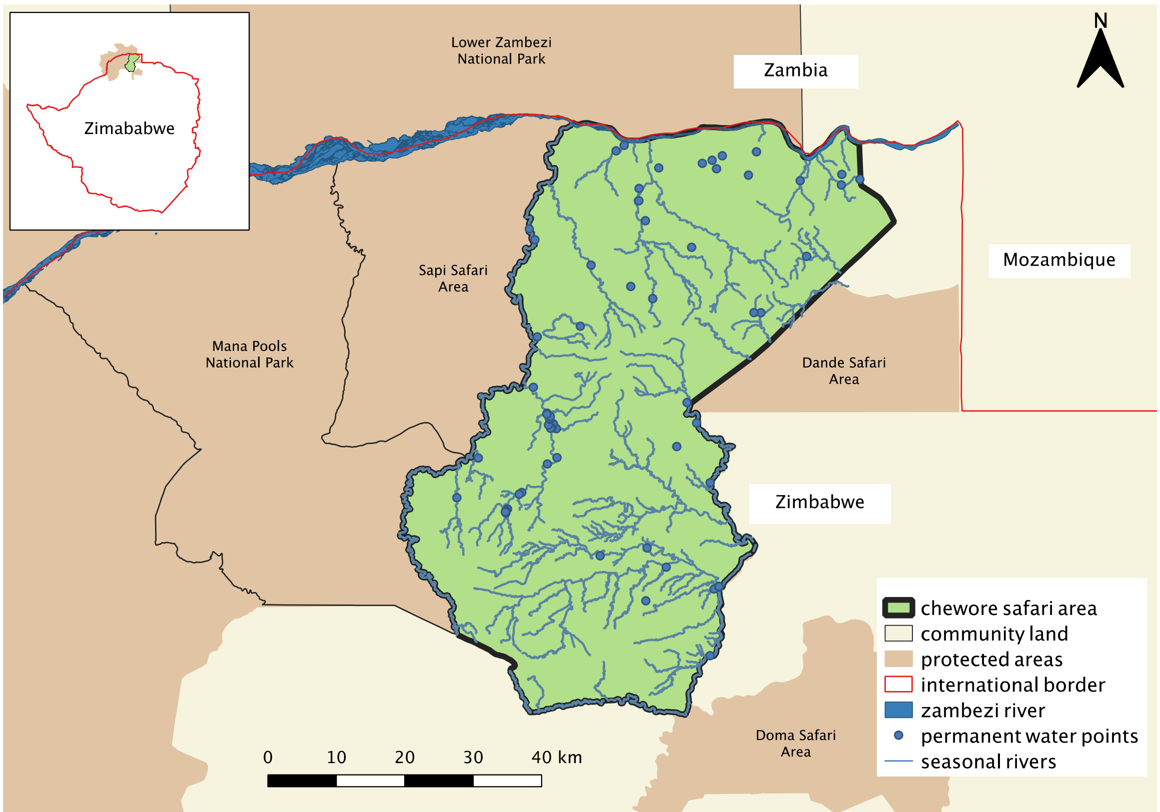



**Figure 3.1.** Study area: The Chewore Safari Area in the Zambezi Valley region of northern Zimbabwe.

*Participatory modelling*

I engaged practitioners to help build and evaluate spatial ensemble models of elephant poaching, with different scenarios to account for ranger patrol bias. Practitioners were engaged at two stages: (1) model construction, and (2) model interrogation (Fig. 3.2). More details are provided under the subheadings below.

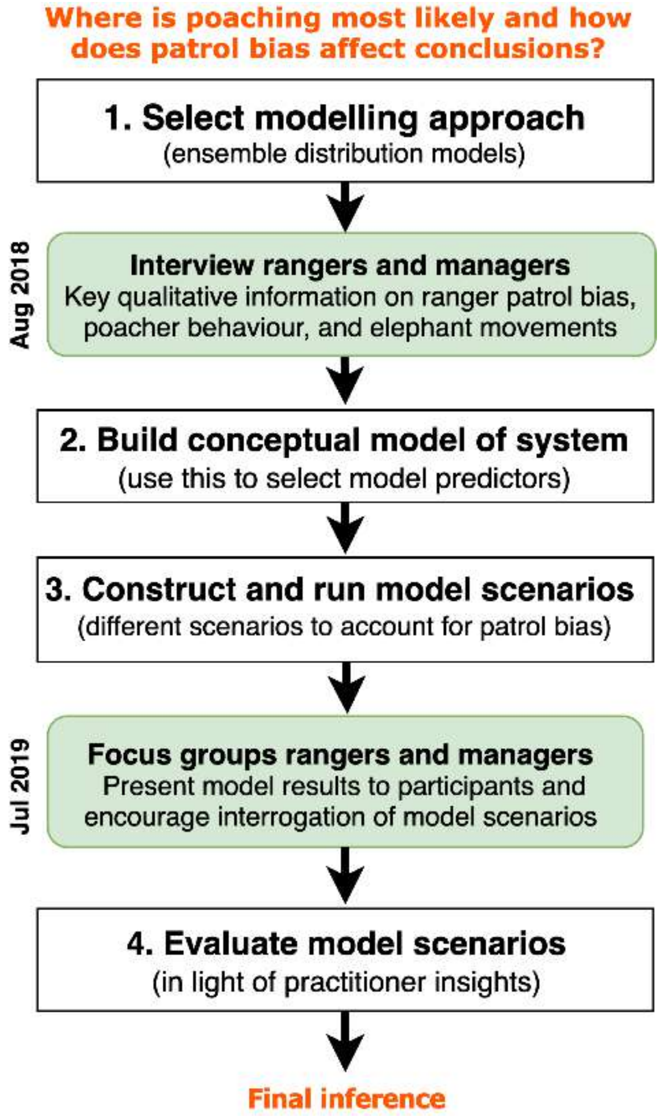



**Figure 3.2**. The participatory modelling approach by stages, showing where practitioners contributed to model building and interrogation. Preliminary interviews with rangers and park managers were used to build a grounded understanding of poacher, ranger and elephant movement dynamics, and better understand spatial patrol patterns and bias. This aided model construction. To discern among the different modelling scenarios, results were presented to rangers and managers who critically interrogated model predictions based on their on-the-ground experience.

*Elephant mortality data*

Rangers recorded elephant carcasses encountered during patrols (Jan 2000 - Dec 2017). Rangers recorded both poached (n=201) and other (n=390) elephant mortalities (the latter including natural, sport-hunted, and problem animal-control mortalities, as well as carcasses categorised as 'unknown mortality'). Several patrol types were employed, the most common being seven-day extended patrols away from ranger stations, during which rangers either moved between temporary bases on a daily basis or remained at the same base for the seven-day period. Also, one ranger was always present on each sport hunting trip (7-21 days), with poached and natural mortalities occasionally encountered. The cause of death, the GPS location of the carcass, the sex and age category of the animal when it died, the age (state of decomposition) of the carcass, and the status of the ivory (removed or present) were recorded (MIKES Programme, 2015).

*Ranger and manager insights for model construction.*

Before model construction, I conducted semi-structured interviews with 14 rangers and four managers at two ranger stations in Chewore in August 2018 (see Chapter 5 for details). Each participant was interviewed individually in a private room, with interviews lasting between 30 minutes and 2 hours (average 58 minutes). Rather than seeking to elicit particular answers, I sought to stimulate discussion by asking broad questions in three main areas:

(a) Ranger patrol patterns: questions around spatial patrol strategies, fine scale patrol patterns, stories of recent patrols, and areas difficult to access by patrol.
(b) Perceived patterns of poacher behaviour: questions around perceived hotspots of poaching, and perceived poacher strategy.
(c) Observations of elephant movements: questions around local knowledge of elephant movements and habitat preferences.

Next, a conceptual framework of factors affecting the distribution of detected poached elephant carcasses was developed based on these qualitative data and the broader literature (Table 3.1; Fig. 3). Respondent descriptions of patrol patterns also provided valuable context to help develop the quantitative scenarios for accounting for patrol bias. Interviews were audio-recorded and transcribed, followed by focussed coding to identify patterns of meaning in relation to the factors of interest (patrol patterns, elephant movements, and poacher behaviour) (Newing, 2010).

**Table 3.1.** Predictors of the spatial distribution of poached elephant carcasses detected by rangers, with their hypothesised effect on elephant, ranger and poacher behaviour. Variable selection was guided by interviews with rangers and managers (statements marked with *), as well as the academic literature. Blank cells are where there is no prior hypothesis. Detail on the data source for each variable is included in the supplementary material.

| Predictor | **Elephant behaviour** | **Ranger behaviour** | **Poacher behaviour** |
|---|---|---|---|
| Distance to (km): | | | |
| River (mostly seasonal) | Surface water availability a strong determinant of elephant ranging patterns in similar systems (Redfern et al., 2003) | Occasionally conduct river patrols or use rivers for navigation* | |
| Permanent water (mostly springs) | As above | Perceived as hotspots for poaching and therefore frequently patrolled. Also, need access to water on extended patrols* | |
| Road | | May occasionally use roads for navigation* | Accessibility and navigation |
| Communal land (human settlement) | May avoid areas nearer densely populated communal areas (particularly the southern boundary of Chewore)* | | Infiltration point, affects travel cost and accessibility (Beale et al., 2017). See Figure 3.1. |
| International border | | | Poachers from Zambia and Mozambique documented* |
| Ranger camp | | Often patrol more intensely nearer camps due to logistical constraints (e.g., vehicle limitations)* | Avoid ranger camps to minimise detection (Beale et al., 2017; Moore et al., 2018) |
| Elevation (m) | Elephants generally avoid high, steep elevations due to poor navigation, but avoid low-lying muddy areas during the wet season (see TRI below)* | Highest elevations infrequently patrolled due to logistical challenges (steep and difficult terrain)* | Higher elevations are difficult to access and navigate through* |
| Topographic Wetness Index (TRI) | Measure of soil moisture and thus forage availability (Redfern et al., 2003). Elephants may avoid wet/muddy areas due to slow navigation and risk of getting stuck* (Douglas-Hamilton and Wall, 2008) | Patrol extent is limited in the wet season due to muddy/flooded roads that are not navigable by vehicle* | |
| Slope | Harder to navigate steeper areas. | Harder to patrol if slope is higher* | Harder to navigate areas of steeper slope* |
| Percentage Tree Cover | Forage availability (Asner et al., 2016) | Harder to detect carcasses in woodland* (O'Kelly et al., 2018) | Cover for poachers (Sibanda et al., 2015) |
| Normalized Difference Vegetation Index (NDVI) | Proxy for forage availability. Indicator of elephant abundance in other studies (Duffy and Pettorelli, 2012) | Harder to detect carcasses in thicker vegetation* (O'Kelly et al., 2018) | Provides cover. May also obstruct poacher movement and lower elephant visibility |

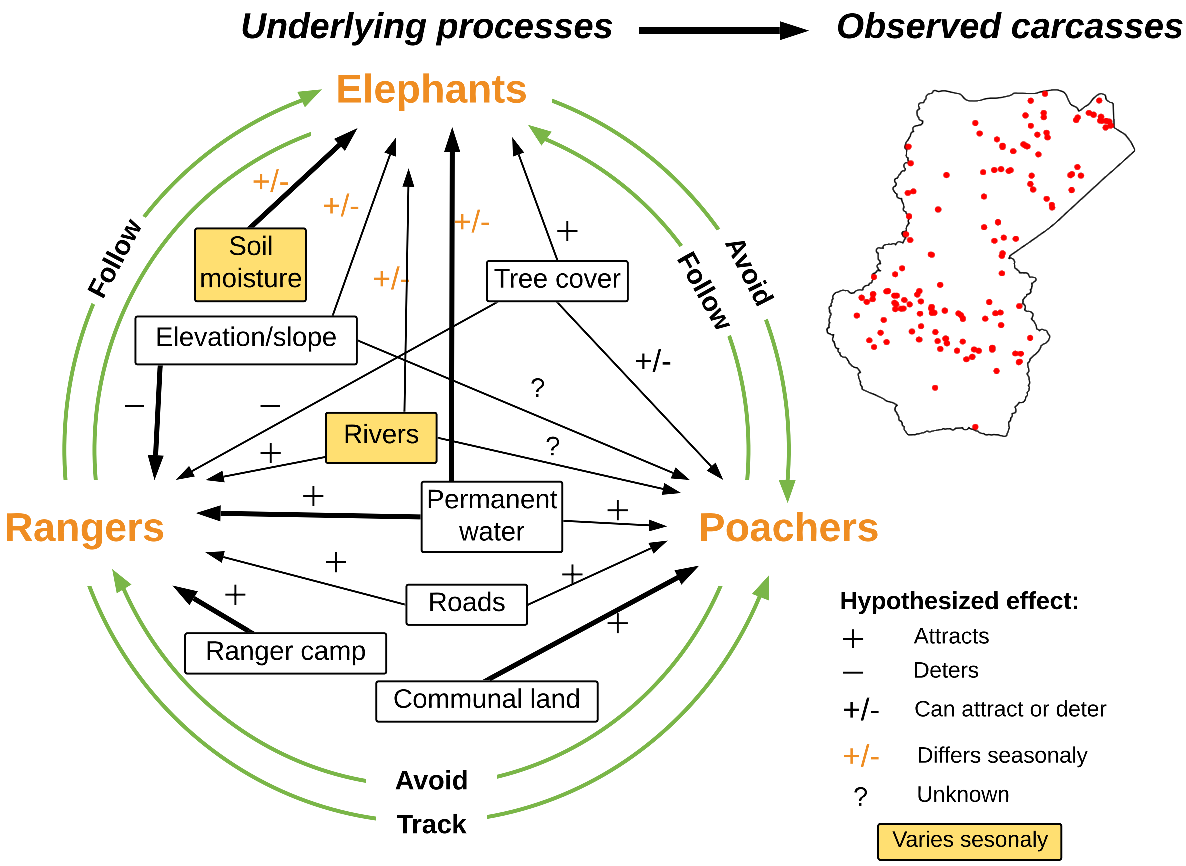



**Figure 3.3.** A conceptual diagram showing the processes underlying the observed distribution of poached elephant carcsses detected by rangers, based on ranger and manager interviews as well as the literature (information sources and references in Table 3.1). I hypothesized that the behaviours of all three agents (elephants, rangers and poachers) are affected by both other agents and certain environmental and anthropogenic spatial predictors (square boxes). Line thickness represents the hypothesized relative strength of the association.

*Ensemble distribution models*

I employed ensemble species distribution modelling (Thuiller et al., 2009) to relate the distribution of detected poached elephant carcasses to the spatial variables identified above (Table 3.1). In total, 187 poached carcasses had accurate location data and so could be used in the models. Details on the datasets used for predictors are in the supplementary material at the end of this Chapter, along with raster plots showing their values across Chewore (Fig. 3.S1). Ensembles have the advantage of incorporating results from a range of modelling techniques based on their explanatory power, frequently performing better than single models (Araújo and New, 2007; Marmion et al., 2009).

The locations of poached carcasses were compared to randomly generated background locations. Following Barbet-Massin et al., (2012) I generated 1000 absences across Chewore. I used a set of four machine-learning algorithms (including random forests and generalised boosted models) and four regression techniques (including generalised linear and additive models) to build my ensembles (see supplementary material). I used the R package *'biomod2'* for analysis (Thuiller et al., 2016). For model evaluation, the full dataset was randomly divided into training and test datasets using a 70:30% split, with 20 different training sets produced by repeated splits (thus capturing model uncertainty). Thus 140 single models were run (seven modelling techniques x 20 splits). Model accuracy was measured using the area under the receiver operating characteristic curve (AUC) as well as the True Skills Statistic (Thuiller et al., 2009). Only those single model runs which performed well (>85% of the AUC of the highest single model run) were used in the ensemble by weighted average consensus (Marmion et al., 2009). Predictor pairs with correlations r>0.60 were excluded (Dormann et al., 2012). Predictor strength in explaining carcass distribution was determined using 'variable importance' (the correlation between the prediction of the full model and a model without the predictor in question; Thuiller et al., 2009)

*Accounting for patrol bias*

Background data in species distribution models are often sampled randomly from the full study area, whereas sampling of occurrence data is often spatially biased (focussed on certain areas), leading to biased inference (Marmion et al., 2009). Ranger patrols are a typical case, given how variable they are in time and space (Critchlow et al., 2015). In such contexts, Barbet-Massin et al. (2012) recommend using geographically-biased background data sampling to match sampling bias.

Phillips et al. (2009) achieve this by using as background data a 'target group' of occurrences of additional observations obtained through similar sampling methods, and thus with similar bias. They show, for 226 species from diverse global regions, that target group sampling significantly improves model performance. Mathematically, occurrence records are not samples from the true distribution of poached carcasses ($\pi$), but from the distribution $\delta\pi$, where $\delta$ is the biased sample distribution (e.g., ranger patrols). The target group represents a set *S* of independent samples from $\delta$, so when it is used as background data the resultant estimated distribution approaches the true distribution $\pi$, for large *S* (Phillips et al., 2009). MIKE data are useful here because rangers record other (natural, unknown, and management-related) elephant mortalities while on patrol, providing a useful target group. I used the location of other mortalities detected by rangers in Chewore over the long term (2000-2017, n=318 records) as a surrogate for patrol locations. A caveat is that the unknown mortalities may contain poached mortalities, but this number is probably low because poached carcasses are mostly detected early, and evidence of poaching is clear. To understand the effect of patrol bias on conclusions about spatial patterns in poaching, I produced three scenarios of background data sampling: a null scenario and two bias-corrected scenarios:

(1) Null scenario: generate background points across the entire polygon of Chewore.
(2) 'Target group' scenario: non-poaching elephant mortalities used as background data.
(3) 'Circular buffer' scenario: generate background data within a buffer of known patrol locations.

The latter two bias-corrected scenarios mitigate against concluding that an area is free of poaching when it is in fact simply seldomly patrolled. For (3), I generated background points within a patrol region defined by circular buffers around confirmed patrol locations (all locations where carcasses were detected, both poached and other mortalities; n=557). This approach is intermediate to the target group and null scenario in that background locations are constrained by confirmed patrol locations, but also generated more widely. Thus, data from regions where rangers are likely to have been present, but where their location was not formally recorded through a carcass record, are included. Three buffer diameters were chosen (1, 3, and 6km) to adequately represent a range of assumptions about true ranger patrol patterns. Thus, five background data sampling sets were generated (Fig. 3.4). I generated the same number of random points within each circular buffer so that more points were generated in areas with more confirmed patrolling (Fig. 3.4).

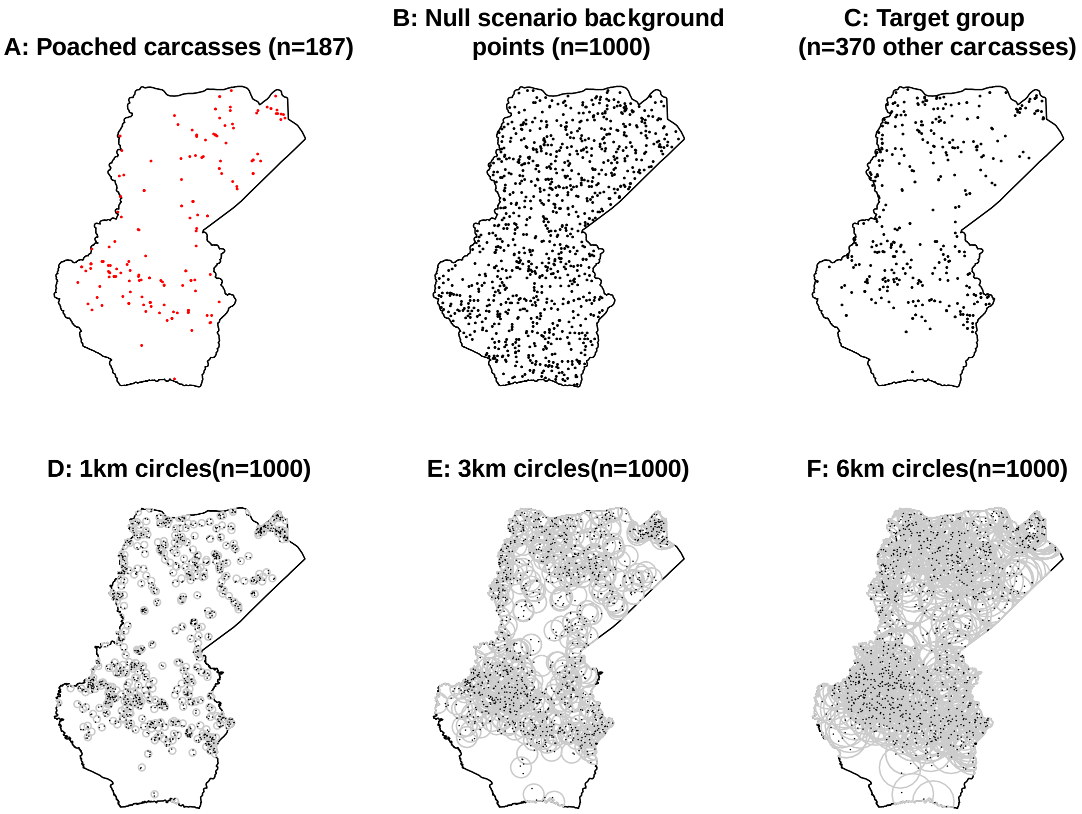



**Figure 3.4.** Different scenarios to understand the effect of patrol bias on spatial patterns in elephant poaching. The distribution of (A) poached carcasses in Chewore (2000-2017), (B) the null scenario background data, (C) the target group scenario background data (non-poaching elephant mortalities), and (D-F) the background data for the circle method with different buffer radii.

I acknowledge that a more robust approach to accounting for patrol bias would be to directly weight model predictions by fine scale patrol effort data, using approaches like hierarchical modelling (as in Critchlow et al. 2015). Such data were however not available at my site. Indeed, in many developing country protected areas, patrol effort data are seldom consistently and reliably available over wide areas and time periods (Dancer, 2019).

*Rangers and mangers interrogate model predictions*

Results from the various modelling scenarios were presented to two separate groups of rangers and managers at two ranger stations in Chewore in July 2019, using a focus group format (Newing, 2010). Participants included eight rangers and two managers at Kapirinhengu base, and seven rangers and one manager at Mkanga base (average experience at site: 5 years). A large computer screen was used to present graphs and maps of the modelling results to each group, with a focus on the graphs of the effect of each spatial predictor on the probability of poaching (Fig. 3.5 below). Participants were encouraged to interrogate model predictions, giving reasons for supporting or not supporting predictions. This led to extensive discussions about the credibility of the different scenarios. Responses were audio-recorded and transcribed, followed by coding relevant to the theme of model interrogation (Newing, 2010). Interview protocols were reviewed and approved by the Human Research Ethics Committee at Oxford University (CUREC REF: R58336/RE001**).**

*Critical reflection on model scenarios*

The final stage involved the lead author critically reflecting on the strength of the different modelling scenarios in light of both practitioner responses to their predictions and the internal logic and assumptions of each scenario.

## 3.3. Results

In all scenarios, the random forests and generalized boosted models performed best at predicting poached carcass distribution (AUC/TSS scores, Fig 3.S2 supplementary material). The ensemble model in each scenario performed markedly better than the single models (Fig. 3.S2). NDVI and tree cover were correlated (r=0.69). I excluded NDVI because it varies widely between seasons whereas the models averaged 17 years of data. All other predictor pairs had r < 0.6.

The effect of each predictor on poached carcass distribution varied according to the scenario of bias-correction (Figures 3.5 and 3.6). In the target group scenario, poached carcasses were detected with higher probability at higher elevations, lower topographic wetness, further from ranger camps, and closer to communal land (while distance to rivers and permanent water had no effect; Figures 3.5 and 3.6). Distance to permanent water and rivers were the strongest predictors in the null scenario (Figures 3.5 and 3.6). The buffer scenario predictions were intermediate between the target group and null scenarios, with elevation and wetness becoming increasingly less important and distance to water and rivers becoming more important from the 1km (most like the target group scenario) to the 6km (most like the null scenario; Figures 5 and 6) scenario. The variable importance scores were low for most variables in each scenario (<0.05). The combined effect of predictors is represented in the probability maps of poached carcass distribution, with different approaches to bias-correction leading to different inferred patterns (Fig. 3.7).

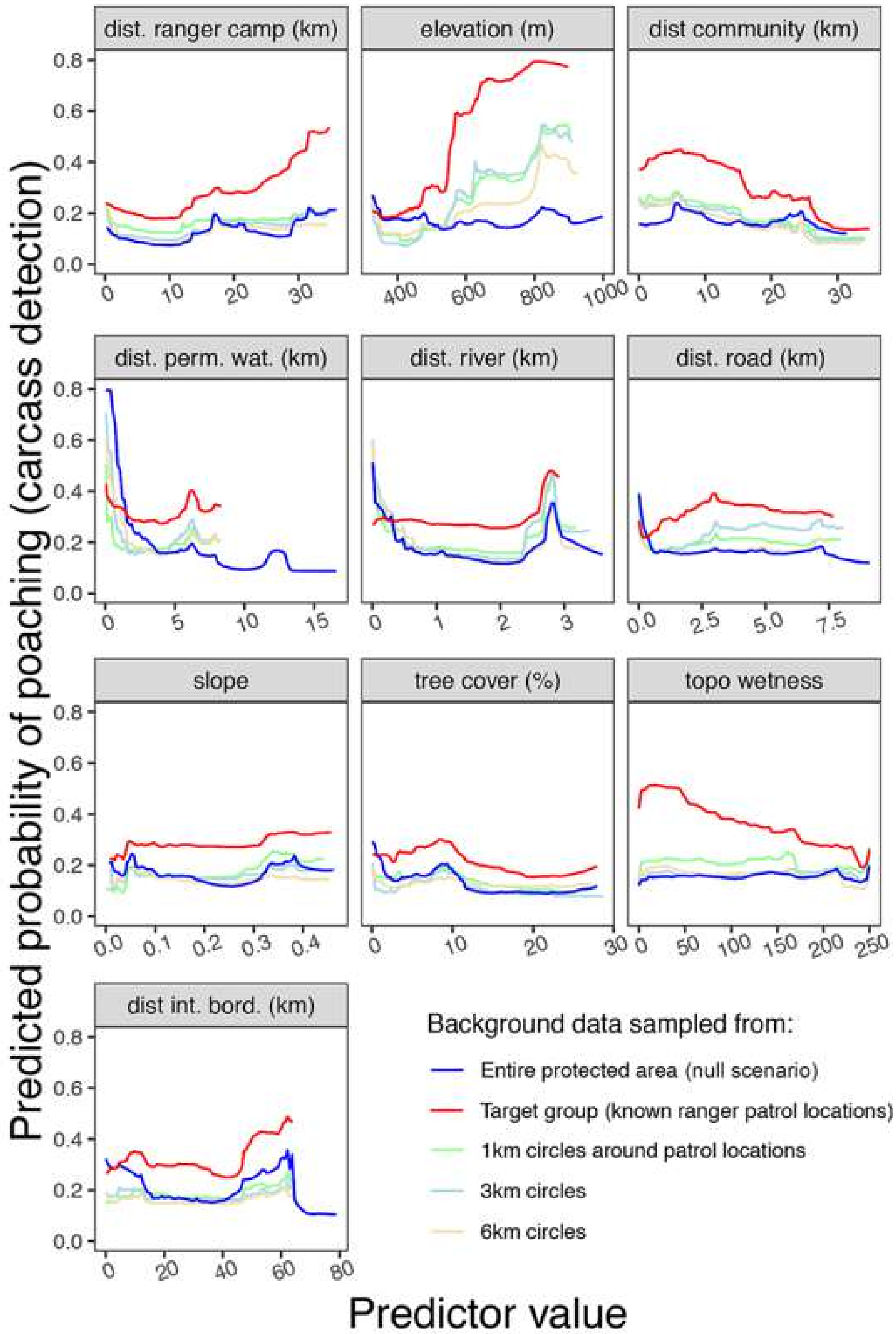



**Figure 3.5.** The spatial relationship between the probability of elephant poaching and each of 10 environmental and anthropogenic predictors, for each scenario of background data sampling. The lines for each scenario are derived from an ensemble model representing the consensus among the top performing of 140 single model runs (7 model techniques with 20 iterations each).

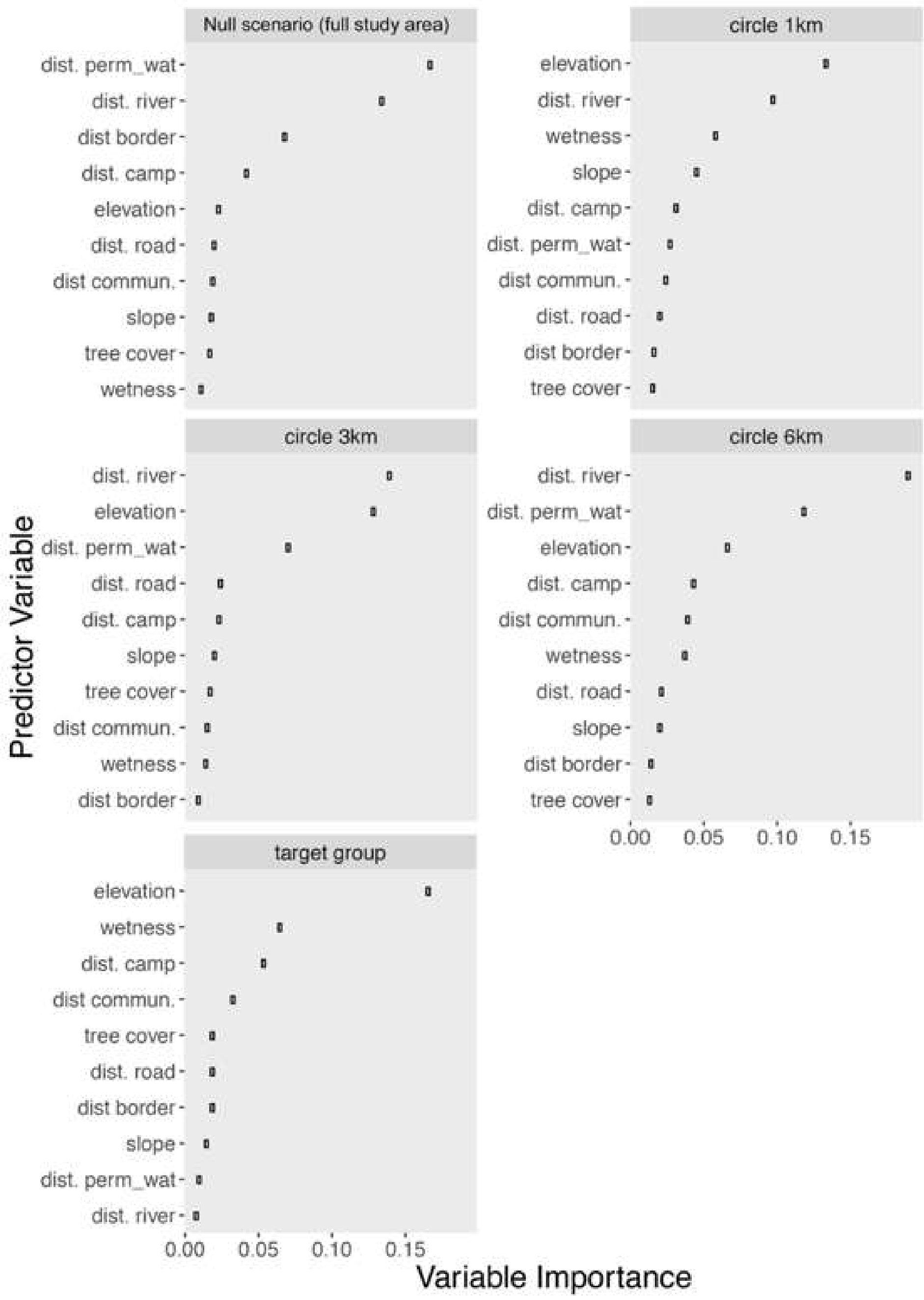



**Figure 3.6.** The variable importance (VI) scores for each of the predictors in the ensemble model in each scenario of background data sampling. VI scores are computed as 1- r, where r is the correlation coefficient between the predictions of the model without the predictor in question. Note that values are comparable among predictors within a model, but not among models. Refer to Table 3.1 for details on each variable.

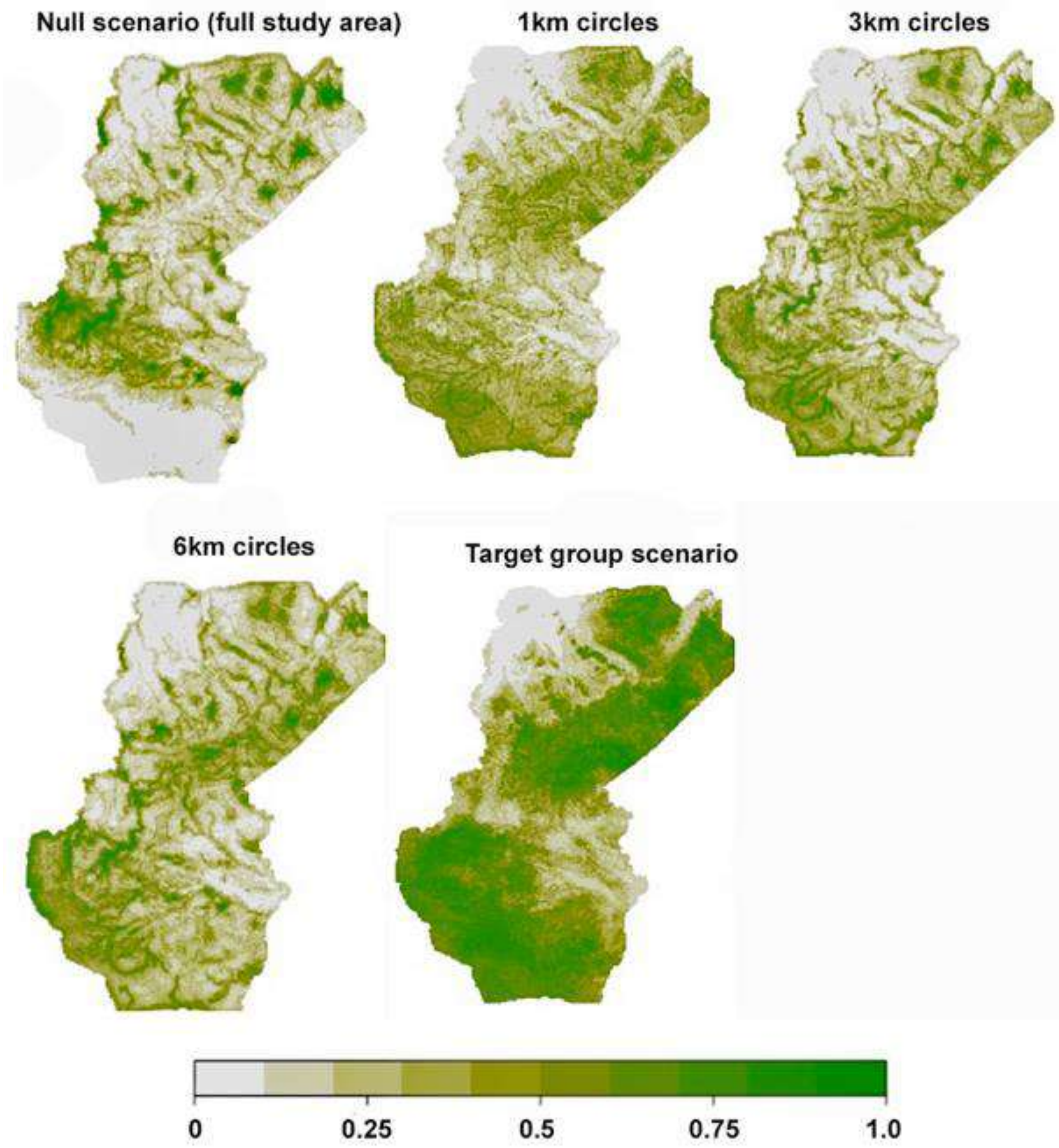



**Figure 3.7.** The relative probability of elephant poaching across Chewore Safari Area based on caracsses detected by rangers, for each scenario of background data sampling. Predictions in each scenario are based on an ensemble model representing the consensus among the top performing of 140 single model runs (7 model techniques with 20 iterations each).

*The influence of patrol monitoring bias*

The shape (Fig. 3.5) and strength (Fig. 3.6) of the effect of each predictor on spatial patterns of poaching differed between the null and bias-corrected scenarios, providing evidence for how patrol bias influences inference about spatial patterns of poaching. In particular, the large differences in the effect of elevation among the different scenarios suggest that that elevation has a strong influence on ranger movements, and hence spatial patterns in what they observe. This accords with rangers own descriptions of avoiding hilly areas (see below). Overall, however, many of the predictor effects did not differ significantly among the scenarios, suggesting that patrol bias may not have as large an affect as originally expected. Small differences did combine to produce larger differences in final predictions, however, as evidenced by the quite different spatial patterns shown in Figure 3.7.

*Rangers and managers interrogate model predictions*

More time was spent discussing the distance to water and elevation effects as these were simultaneously the strongest and most contentious. The target group predictions were the most strongly questioned by rangers and managers. The predictions of higher levels of poaching at higher elevations, and the absence of distance-to-permanent-water and distance-to-river effects, were particularly challenged because they did not make sense in light of rangers' understanding of elephant distribution, developed over multiple years. Participants described routinely tracking elephants, *"that is the tactic we use, we follow the elephants…so when the poachers want to poach an elephant we will be there"* (R4). "*We focus where there is more concentration of elephant*" (R11). Participants agreed that poachers target areas where they can reliably find elephants, *"Where elephants are more concentrated, there are poachers there"* (R9).

There was strong consensus among participants that elephant abundance was low at high elevations: *"The area is mountainous, so it is very difficult for elephants to navigate, so they avoid it"* (R13). When questioned whether carcasses (poached and other) in mountainous areas remain undetected because patrols avoid these areas, rangers again invoked elephant distribution. While admitting they spend little time at higher elevations (*"the area is very difficult for rangers to access and patrol"* [R6]), rangers said that when they do visit these areas, they find little evidence of elephant presence (visual, spoor, etc.). *"There might be some poached carcasses in the mountains, but the probability is very low…the area is difficult for animals and people"* (R1). Rangers also suggested that mountains limit poacher access; *"those mountainous areas…even the poachers can hardly move there"* (R16). Rangers also pointed out that the extensive mountain escarpment along the southern boundary of the park (see supplementary material Fig. 3.S1, elevation) is adjacent to densely populated communal land. Human incursion into Chewore for bushmeat hunting and wood collection was described as another reason why elephants avoid the mountains. Finally, they referred to a 2014 aerial survey which reported very few live elephants or carcasses in the mountainous regions (Fig.

3.S3 supplementary material). Thus, while low patrol effort may play a role, low carcass detections at higher elevations is likely to be principally driven by low elephant abundance.

Participants repeatedly cited permanent water points as key hotspots for elephant abundance and poaching, and thus ranger deployments. *“We go along covering the water points... because poachers don’t go where there are no animals…so we concentrate on those areas. Elephants don’t move very far from water”* (S2). *“Elephants are abundant there because of water”* (R15). Participants therefore supported scenarios that predicted high levels of poaching near permanent water (the null and circular scenarios), and strongly questioned the weak distance-to-permanent-water effect in the target group scenario. They were similarly unsupportive of the neutral distance-to-river effect on poaching in the target group scenario, while supporting the positive effect observed in the circular buffer scenarios (again due to elephant distribution). *“These elephants will be moving along those riverine areas looking for those ilala palms, most rivers have ilala palms…elephants love those… they also like the shade of the riverine vegetation”* (S3). Rangers do not routinely patrol along rivers (*“Most of the time we don’t follow roads and rivers because you can be easily detected”* [R1]), suggesting therefore that this effect is not due to patrol bias.

*Critical reflection on modelling scenarios*

Elephant distribution effects on poaching patterns was a common thread in participants’ responses, suggesting that elephant distribution is a strong driver of spatial patterns in poaching. This led to my critical reflection on the target group method, exposing a particular weakness. The target group background dataset is composed of elephant carcass locations and is therefore heavily dependent on elephant distribution. By comparing poached carcass locations to the locations of other elephant mortalities (which may be considered a coarse proxy of live and poachable elephant distribution), the effect of elephant distribution on poaching patterns is controlled away. This explains the predictions of higher-than-expected levels of poaching in areas of low perceived elephant density (higher elevations) and lower-than-expected levels of poaching in areas of perceived higher elephant density (near water). Thus, while the target group may act as a proxy for patrol locations and bias, it negates elephant abundance effects. This is problematic for managers, because anti-poaching strategies should target areas of higher poaching regardless of the underlying cause (in this case, higher elephant density). Conversely, greater practitioner support for the predictions of the circular buffer scenario may be because it is a better reflection of reality. This may be because using random locations within the vicinity of carcass detections is a robust approach to accounting for patrol bias (unlike the null scenario), while not being too tied to elephant distribution (as in the target group scenario).

## 3.4. Discussion

Uncertainty is recognised as an important topic within socio-ecological systems research. These systems comprise complex and uncertain linkages between human behaviour and natural systems (Milner-Gulland and Shea, 2017). In line with this, applied ecologists are developing more robust tools for dealing with one particular class of uncertainty: observation uncertainty, the discrepancy between the true and observed states of the natural system under management (Bunnefeld et al., 2017). However, we should be careful not to introduce another class of uncertainty, through modelling bias, in our quest to correct for observation uncertainty. This Chapter demonstrates the power of combining statistical tools to correct for observation bias with participatory approaches to guide us away from model bias, thereby reducing uncertainty in inference on spatial patterns of poaching. Using practitioner perspectives and the literature to generate hypotheses to guide model construction, and then comparing the different scenarios generated by the model with practitioners, helped us tease apart real patterns from those explainable either by patrol bias, or by model assumptions. Bias correction and qualitatively-guided model interpretation revealed water distribution as a key driver of poaching patterns.

*Patrol bias and inferred spatial patterns of poaching*

Our second research question sought to understand how spatial patrol bias affects conclusions made from patrol observations. Overall, the differences in the predictions of the null and bias-corrected scenarios indicate that patrol bias does indeed influence inferred spatial patterns of poaching. In particular, the avoidance by rangers of higher elevation areas had a large effect on conclusions drawn (see below). Apart from elevation, however, the predictions of the null and circular buffer scenarios were similar for most other predictors (Fig. 3.5), suggesting either the buffer scenario does not adequately account for bias or the effect of patrol bias on inferences may in fact not be large. The fact that the 1km buffer predictions (reflecting the strongest assumption about patrol bias) were similar to those of the null scenario predictions suggests the latter may be true. Carcass data are aggregated from 17 years of patrols, so many of the carcasses from elephants poached outside heavily patrolled regions would eventually be detected, thus reducing patrol bias effects. While both the target group and circular buffer scenarios aim to account for patrol bias, both are influenced to some degree by elephant distribution as they rely on elephant carcass data. Practitioners helped us discern that this was more of a problem for the target group method, with the circle method less affected.

*Practitioners help distinguish true patterns from those explained by patrol bias*

The marked effect of higher predicted levels of poaching closer to water in the null scenario was weaker in the target group scenario, suggesting that the effect may be due to high patrol intensity near water. The water effect remained positive in all three scenarios that corrected for patrol bias through circular buffers, suggesting that higher detections near water are not solely due to patrol bias. This result, together with practitioner insights (which favoured the circular buffer method and pointed to predictable elephant abundance near water) suggests that higher detections of poaching near water may in fact primarily be driven by elephant distribution. Practitioners explained these patterns as poachers targeting water sources as sites of high and predictable elephant abundance. This result is in line with previous studies: Sibanda et al. (2015) predicted higher levels of elephant poaching near rivers in a Zimbabwean protected area. Beale et al. (2017) similarly found elephant poaching to correlate with elephant abundance in the Ruaha system in Tanzania, while Critchlow *et al.* (2016) found that spatial hotspots of large animal poaching in a Ugandan PA to coincided with high density of target species.

The higher predicted levels of poaching at higher elevations in the target group scenario, questioned by practitioners, was also likely also due to the target method weakening the effect of elephant distribution. This argument cannot however explain why all the circular buffers scenarios also predicted a positive, albeit weaker, elevation effect. Rangers said that they rarely patrolled higher elevations due to navigation challenges, so the bias-corrected methods will have better captured the true bias in ranger patrols by excluding the infrequently patrolled highest elevations. Thus, the existence of an elevation effect seems credible, despite practitioner objections and lower elephant abundance at higher elevations. This demonstrates how, while practitioners must rightly interrogate model predictions, non-intuitive model predictions must also be allowed to challenge practitioner experience. Background data in all the bias-corrected scenarios was, however, scant at the highest elevations (>800m), so extrapolation of a positive elevation effect to these highest elevations may be tenuous.

*Do we trust models or practitioners?*

Model results should not simply be disregarded if their predictions are non-intuitive to those with intimate knowledge of the systems they represent. Otherwise, modelling would simply be a confirmatory exercise. A strength of quantitative models is their ability to predict outcomes of complex interactions that would be impossible to predict non-mathematically (Dobson et al., 2018). Models might also be more objective than practitioner predictions (Addison et al., 2013). For example, practitioners may fall into a confirmation trap whereby perceived poaching hotspots are reinforced by intense patrolling. On the other hand, model predictions are only as good as their input data and assumptions. The sensitivity of predictions to the different scenarios of background data sampling  in this study is illustrative of this. Practitioners helped identify a weakness in the target group modelling scenario which may otherwise have gone unrecognised. Participatory modelling helps minimise those assumptions that are too abstract and identify those that are tenuous, while maximising those that align with on-the-ground reality. The key, then, is to retain the power of models to interrogate data and test assumptions, while not producing insights that are based on abstract notions rather than on-the-ground realities.

*Complex mechanisms and randomness*

The pattern of poached carcasses observed by rangers was produced by a complexity of processes representing the interactiona of elephants, rangers, and poachers with each other and their environment (Fig. 3.3). Ranger presence can, for example, deter poachers and thus override the effect of other spatial predictors (Moore et al., 2018). Furthermore, spatial predictors may be mediated by the effects of agents on each other. If elephants are attracted to water, poachers will learn to target waterholes. Interactions can also involve negative feedbacks; poachers may prefer to use roads for quick access, but rangers may also use roads for navigation, possibly leading to poachers avoiding roads. Without robust data on these behaviours, interpretation of the mechanisms behind observed patterns will be uncertain.

A notable result is the low variable importance scores for most variables (<0.10), showing they had only small effects on poaching distribution. This suggests some level of randomness in the spatial distribution of poaching, with consistent patterns difficult to elucidate. Critchlow et al. (2015) concluded that the lack of strong predictor effects on the spatial distribution of illegal activity may be due to complexity in how these covariates affect poachers and wildlife. The effect of predictors may also change over time or operate at different temporal scales, leading to further complexity. Variation in the spatial pattern of poaching through time (i.e. space-time clusters in poaching at monthly or yearly scales) may have confounded the effects of spatial predictors. The upshot of this randomness and complexity is that the predictors of poacher behaviour can be difficult to unmask, and therefore it may not be possible to make simple management recommendations about patrol targeting.

*Key priorities for future research*

I acknowledge a number of limitations with my analysis. The target group method, while demonstrated to work in other contexts, is a crude measure of patrol effort. A more robust target group will have included the locations of additional ranger patrol observations (e.g., all animal sightings). Ideally, model results would have been weighted by fine grain data on spatial patrol effort. Critchlow et al. (2015), for example, used hierarchical models to develop estimates of the true distribution of illegal activities in Queen Elizabeth National Park in Uganda by combining an occupancy model of detected illegal activities with robust measures of survey effort (per PA grid cell). The effort data needed for these approaches are however only available at well-managed sites with the capacity and resources to collect them (Dancer, 2019). I also do not consider changes in the spatial patterns of poaching among years and seasons - the results presented here represent average effects over several years. In this study, only elephant carcasses detected fresh (66 records) could reliably be assigned to seasons, so robust seasonal ensemble models were precluded. Finally, I do not explicitly account for the effects of elephant distribution on poaching patterns. Aerial survey data from my study area could have been used as a proxy for this, but these surveys sample only 15% of the land area, have only been conducted twice in the last 20 years, and offer only a dry season snapshot of elephant distribution.

*Application to conservation management: implementation in the real world*

Our results demonstrate the importance of accounting for observer bias when drawing inferences from observational data. The patterns of elephant poaching documented here show a high degree of sensitivity to spatial ranger patrol bias. Management strategies, such as the deployment of patrols in areas of highest illegal activity, should not be uncritically based on raw patrol data. Patrol deployments that account for patrol bias can lead to significant gains in detection of illegal activities; Critchlow et al. (2016) demonstrated as much as a 250% increase in detections compared to the baseline, using the same amount of effort and resources. Without some measure of patrol effort, it is impossible to draw robust conclusions about poaching trends and hence predict where and when future poaching might happen. This underscores the importance to PA management of collecting regular patrol effort data at a relevant scale. An obvious challenge is developing capacity and resources for robust data collection. Interviews at my study site show that data collection is only one among many, often more pressing, responsibilities like anti-poaching. The collection and integrated analysis of effort and observational data is a large undertaking that will require a step-change in resource allocation. Ultimately, developing an organizational culture that values and prioritises data collection, analysis and use for adaptive management is perhaps the biggest obstacle to robust monitoring (Field et al., 2007). I suggest that investment in such structural changes is worthwhile. Robust monitoring can also lead to more resource-efficient anti-poaching strategies in the long term. Yet there exists a trade off between allocating resources to more efficient monitoring versus direct anti-poaching (McDonald-Madden et al., 2010). The simple scenarios of patrol bias correction employed here offer promise for spatial analysis at other MIKE sites, since more fine-scale data on patrol effort has already been identified as logistically infeasible at the majority of MIKE sites (Malpas and D´Udine, 2013).

Finally, the participatory modelling approach employed here may prove useful in other socio-ecological research contexts. Both quantitative models and practitioner insights can be biased, so integrating these alternate lines of evidence is likely to lead to stronger evidence and better management (Voinov and Bousquet, 2010). This is important in contexts such as ranger-based monitoring, where data are not collected systematically and where results are of distinct practical relevance (Keane et al., 2011). Participatory modelling is also more likely to lead to actual use of models in conservation management because end users are already engaged and less likely to see models as detached abstractions (Addison et al., 2013). Finally, this work emphasizes the importance of recognising the knowledge and analytical agency of wildlife rangers. Their perspectives should be sought, rather than seeing them as passive implementers of conservation work or science planned by others (Moreto and Lemieux, 2015).

## 3.5. Supplementary material

*Supplementary methods: ensemble distribution models*

A variety of techniques for modelling the distribution of species exist (regression, machine learning, classification techniques, etc.). The literature suggests that the performance of different models is context- and species-dependent (Segurado and Araújo, 2004). I used a set of three regression techniques (generalised linear models [GLM], generalised additive models [GAM], and multivariate adaptive regression splines [MARS]), as well as four machine learning techniques (maximum entropy [MAXENT Tsuruoka method], artificial neural networks [ANN], generalised boosted models [GBM, also referred to as boosted regression trees], and random forests [RF]). Model details are in Thuiller et al. (2009). I chose to exclude other techniques (classification tree analysis, mixture and flexible discriminant analysis (MDA), and rectilinear envelope models) due to consistent and significant low performance in earlier runs.

Elevation and slope were calculated from a digital elevation model (USGS, 2004). I used the SAGA-GIS software to create the wetness index from the elevation model (Conrad et al., 2015). Tree cover data were derived from Landsat 5/7 based rescaling of MODIS satellite imagery (Sexton et al., 2013) while NDVI data were derived directly from the Landsat 7 Tier 1 32-day composite NDVI collection (U.S. Geological Survey). Google Earth Engine was used to extract the mean tree cover value for the period 2000-2010 (the data are not available for later periods), and the mean NDVI value for the period 2000-2017. All layers were available at a native resolution of 30m, and the distance raster layers were created using this resolution. The locations of permanent water points were based on ranger station records, with additional points identified with the help of experienced rangers pointing them out on GIS maps.

Barbet-Massin et al. (2012) suggest using the same number of background and occurrence points for machine learning techniques, and a large number of background points (10 000) for regression techniques. I ran initial tests using 10 replicates (training sets) of each modelling technique for each of five possible numbers of background points (200, 500, 1000, 5000 and 10 000), and computed AUC scores. Scores did not vary widely across the different background sets (differences in AUC <0.05), and for simplicity I decided to use 1000 background points for all analyses as this sample performed best most consistently.

The bias-corrected models had lower predictive accuracy than the models with background data sampled from the full study area (Table 3.3 main text and Fig. 3.S1 below). However, this probably arose because of easier prediction of background points which were generated further from the ranger patrol area when random background sampling was used. Lobo, Jiménez-valverde & Real (2008) have established that AUC is sensitive to geographical extent, such that models with background data further from occurrences have artificially inflated AUC scores. The target group and 1km/3km circular buffer scenarios have extents less than half that of the random background data, so I do not discount the bias-corrected models based on their lower AUC scores.

While the predictive accuracy of all the models was very high, it must be noted that the within-sample model testing (no independent data used) used here tends to provide overly optimistic model evaluation compared to independent data (Araujo et al., 2005).

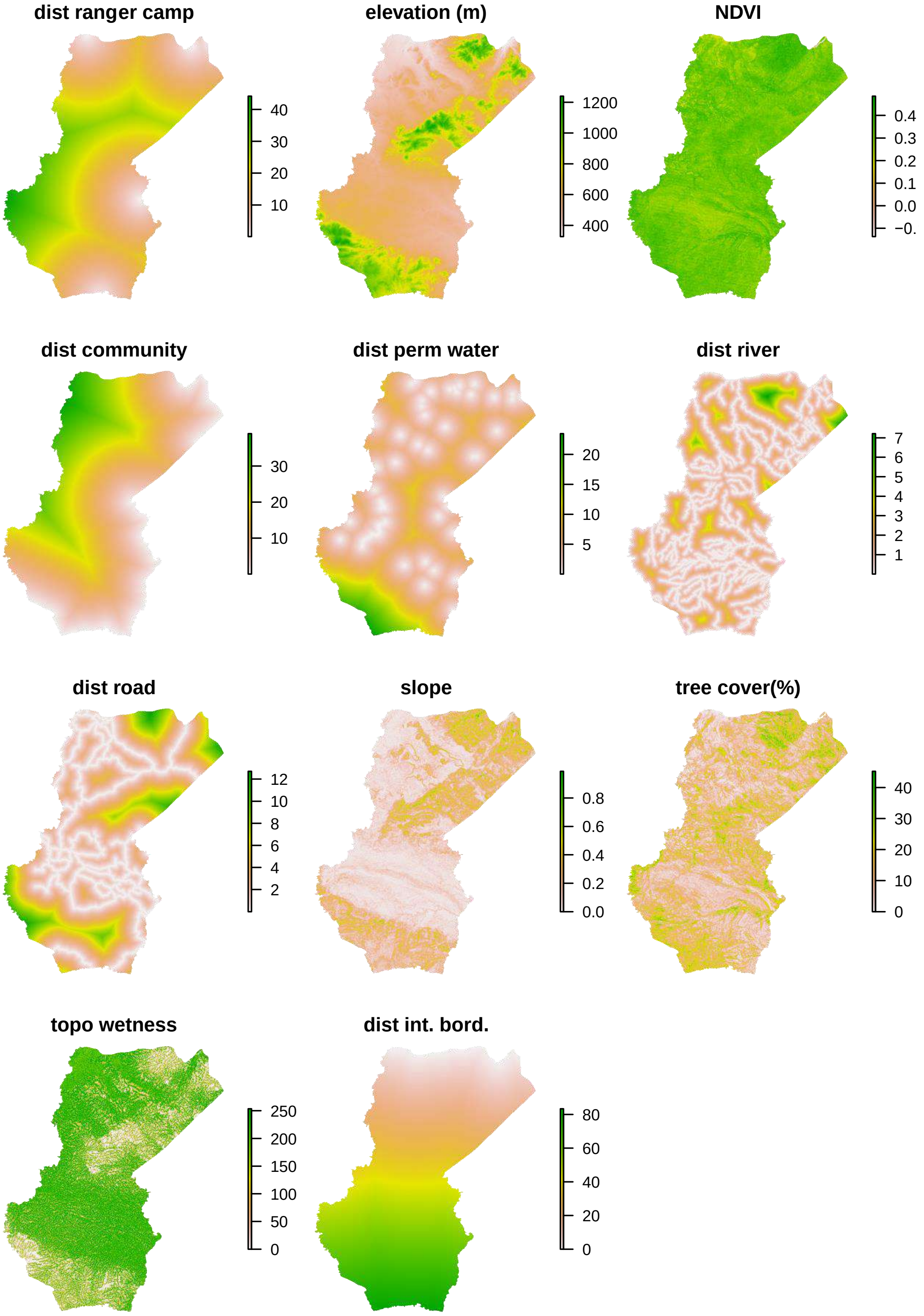



**Figure 3.S1.** The variables used to predict the distribution of detected poached elephant carcasses via the ensemble distribution models. Values for each 30m raster pixel across Chewore are shown. Distances are in kilometres.

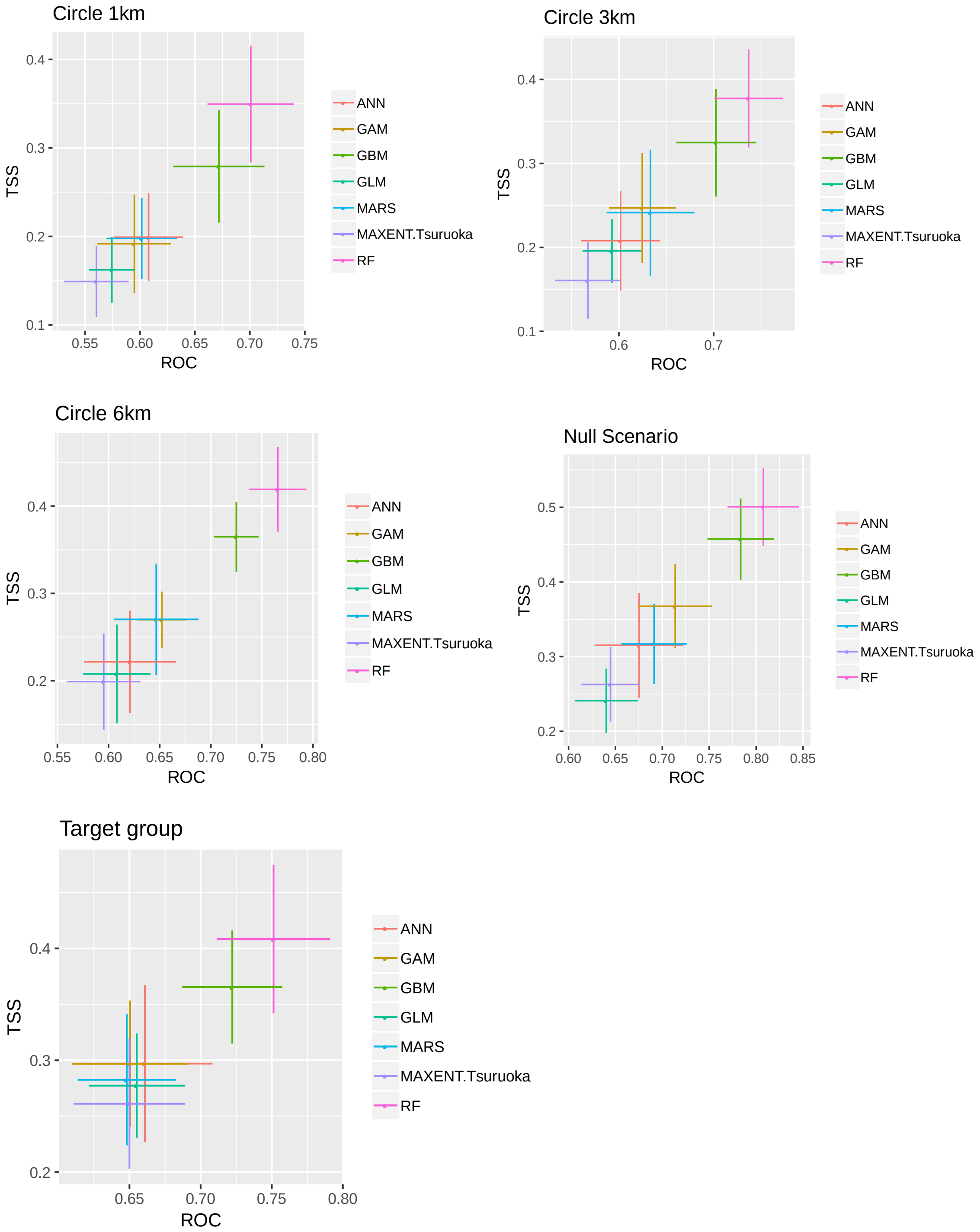



**Figure 3.S2**. Model performance scores (Area Under the Receiver Operating Curve [ROC] and True Skills Statistic) for each of the seven single modelling techniques in each scenario of background data sampling. Mean scores (±SD) across 20 iterations are shown. ROC/TSS values should be compared within, not among, plots (Lobo et al. 2008). RF=random forests, GBM=general boosted models, ANN= Artificial Neural Networks, GLM= Generalised Linear Models, GAM = General Additive Models, MARS = Multiple Adaptive Regression Splines).

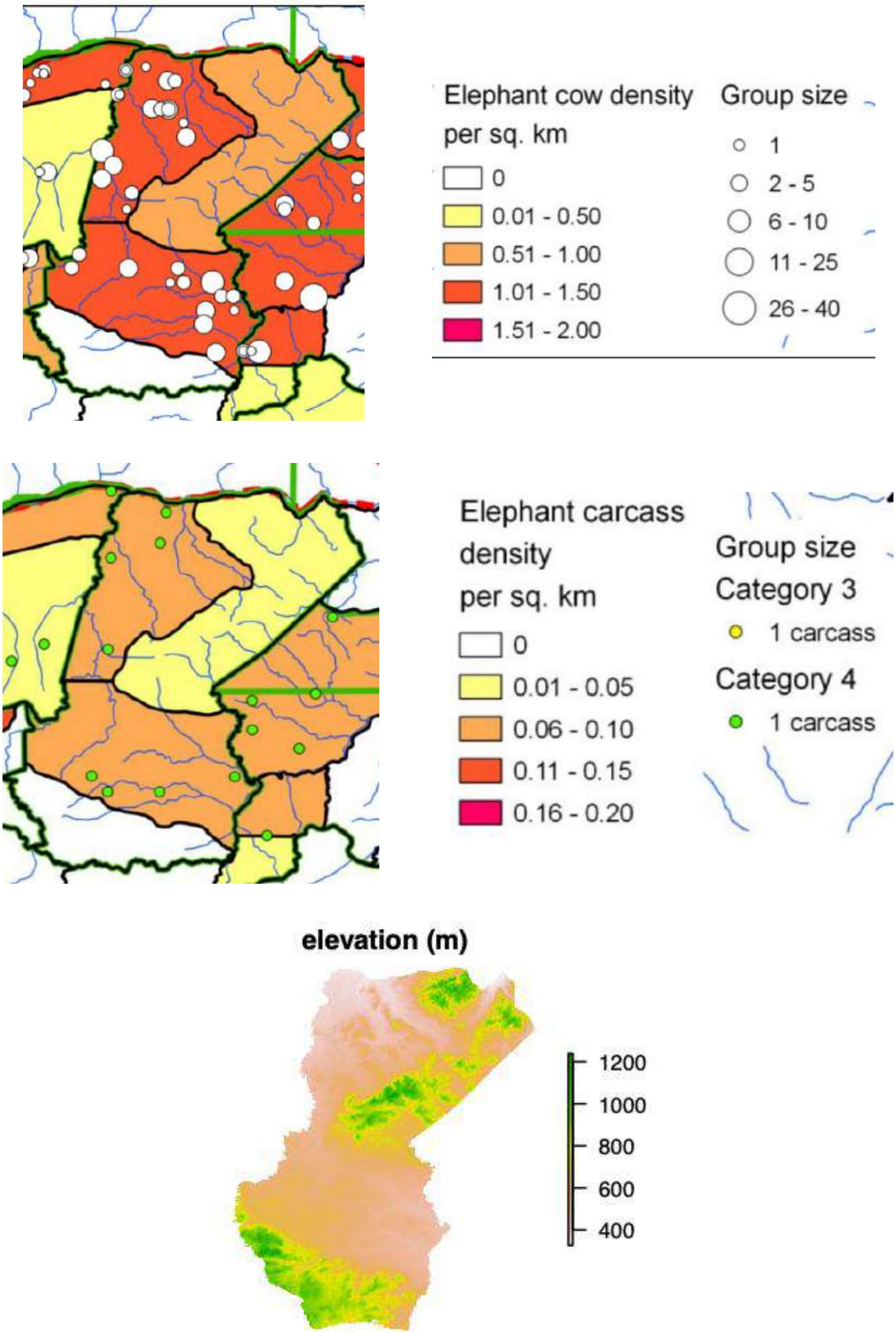



**Figure 3.S3.** The distribution of elephant herds (top) and elephant carcasses (bottom) in Chewore Safari Area based on results from an aerial survey in August 2014 (Figures copied from Dunham et al., 2015). Notice the low density in the mountainous regions (elevation insert). Transect sampling intensity was around 10% of the area, with extrapolation based on the Jolly method (see Dunham et al. 2015 for full details).

# Chapter 4: The reliability of ranger patrols for detecting spatial and temporal trends in elephant poaching

## 4.1. Introduction

Reliable data on trends in biodiversity can help managers and policy makers make decisions that improve conservation outcomes (Canessa et al., 2015). For example, basic data on temporal changes in the prevalence of illegal activities within a protected area can help managers evaluate and improve upon current management strategies (Critchlow et al., 2016). However, as discussed in the introduction of this Thesis (Chapter 1), socio-ecological systems are only partially observable and field monitoring data is often biased and imprecise. This is particularly the case with non-systematic forms of data collection such as ranger patrols or citizen science, where sampling bias may be particularly problematic (Altwegg and Nichols, 2019). This does not mean that “messy” data cannot be useful for conservation, but it is imperative that bias and uncertainty in monitoring data is properly understood and accounted for before conclusions about underlying system processes are drawn (Dobson et al., 2020). Crucially, monitoring programmes themselves (whether systematic or opportunistic) must be carefully evaluated to ensure they have sufficient power to answer key questions that managers hope to ask of them. Given limited resources, monitoring must be designed to meet particular goals (Field et al., 2005; Pollock et al., 2002). One might ask, for example, whether current ranger patrol strategies in a particular protected area are likely to yield poaching data that reliably represent underlying poaching dynamics.

A significant challenge is quantifying data bias and imprecision, identifying which factors most influence them, and understanding how these uncertainties affect our ability to reliably answer key questions from monitoring data. This is because underlying system processes (e.g., the true number of elephants poached in a particular year) are often only partially observed, so it is difficult to know how close monitoring data are to the truth. The virtual ecologist approach described in the methods section of this Thesis (see Chapter 2) presents a promising solution. The approach involves simulating both underlying socio-ecological processes (e.g., elephant poaching), as well as the observation process (i.e., the ranger-based monitoring), thus yielding both the ‘true’ and ‘observed’ states of the system (Zurell et al., 2010). The approach has been used in many different contexts to understand observation bias and optimise the design of monitoring programmes (Ling and Milner-Gulland, 2007; McConville et al., 2009; Nuno et al., 2015; Rachowicz et al., 2006). Nuno et al. (2013) used the virtual ecologist framework to examine the influence of sampling effort and observer biases, as well as simulated population characteristics, on the accuracy and precision of ungulate population estimates from aerial surveys in the Serengeti. Similarly, Jones et al. (2017) simulated virtual ecologists conducting systematic surveys of illegal activities in Gola National Park, Sierra Leone, to test the level of survey intensity required to reliably detect changes in poaching over time.

Crucially, the ‘true’ and ‘observed’ states are in the model, not in the real world. The reliability of virtual ecology model simulations is thus proportional to how well the model represents realistic system dynamics. In the context of this Thesis, I have gathered and analysed quantitative and qualitative data that has helped me build a good understanding of my study system in Zimbabwe, particularly the dynamics of elephant poaching and ranger-based monitoring (see Chapters 3 and 5 in particular). In this Chapter, I use this understanding to build realistic scenarios of elephant poaching and ranger detection of poached carcasses in order to understand the performance of different patrol strategies in terms of capturing underlying patterns in poaching. I also explore how various uncertainties in my understanding of the system and alternative possible ‘truths’ alter my conclusions. My aim is to better understand the drivers of data reliability under realistic scenarios of poaching and patrols, rather than seeking to represent the exact ‘true’ system state. Following Getz et al. (2017), I seek to construct models that are complex enough to capture underlying processes that are hypothesised to affect the accuracy of observations, but not more complex than necessary to answer my research question or too complex for the information used to parameterise them. I first design a generic simulation modelling framework to assess the performance of ranger-based monitoring strategies for answering management-relevant questions around trends in biodiversity or threats. I use the term “virtual ranger model” to describe this framework and design it to be flexible enough for broad application to a variety of different contexts involving rangers patrolling and collecting key ecological data. I then demonstrate the utility of the framework by applying it to ranger-based monitoring of elephant poaching in my case study. The practical outcome of this approach is to provide insights for park managers seeking to manage trade-offs between data reliability and resource allocation.

My aim in this Chapter is to better understand and quantify the factors that influence the reliability of ranger-collected data on elephant poaching (i.e., how well these data capture 'true' spatial and temporal patterns of poaching). Factors investigated include those related to (1) the ranger patrol observation process (e.g., patrol effort, coverage, and spatial pattern), and (2) elephant poaching dynamics (e.g., poaching intensity, temporal trend and spatial pattern of poaching). These two processes are both potentially under management influence and are therefore management relevant. To address this aim, I use the virtual ranger framework to simulate both (a) realistic scenarios of varying elephant poaching intensity across space and time, and (b) realistic scenarios of varying ranger patrol effort and pattern, and carcass detection, across space and time. Given the importance to managers of detecting changes in poaching over time and across space, I measure reliability as the power of various patrol scenarios to identify simulated 'real' changes in poaching across time and space. I develop ranger patrol and elephant poaching sub-models and parameterise them to my case study site based on extensive quantitative and qualitative data.

## 4.2. Methods

*Broad modelling approach*

I followed a two-stage modelling approach to address the above objectives. First, I designed a generic modelling framework to evaluate the performance of different ranger-based monitoring strategies in terms of answering specific management-relevant questions. A particular question might be: "What level of patrol effort is required to successfully detect a 50% decline in elephant poaching that occurs over 2 years?". However, the framework is generic in that it may be applied to answering questions about the role of rangers in collecting key ecological data in a broad variety of contexts. Second, to meet the objectives of this Chapter, I adapt this generic framework to the context of rangers collecting data on elephant carcasses in my study area of the Zambezi Valley, Zimbabwe. I used this case study-parameterised model to test the effect of various factors (related to both ranger patrols and underlying poaching dynamics) on the performance of ranger patrols at detecting spatial and temporal patterns in poaching (Fig. 4.1).

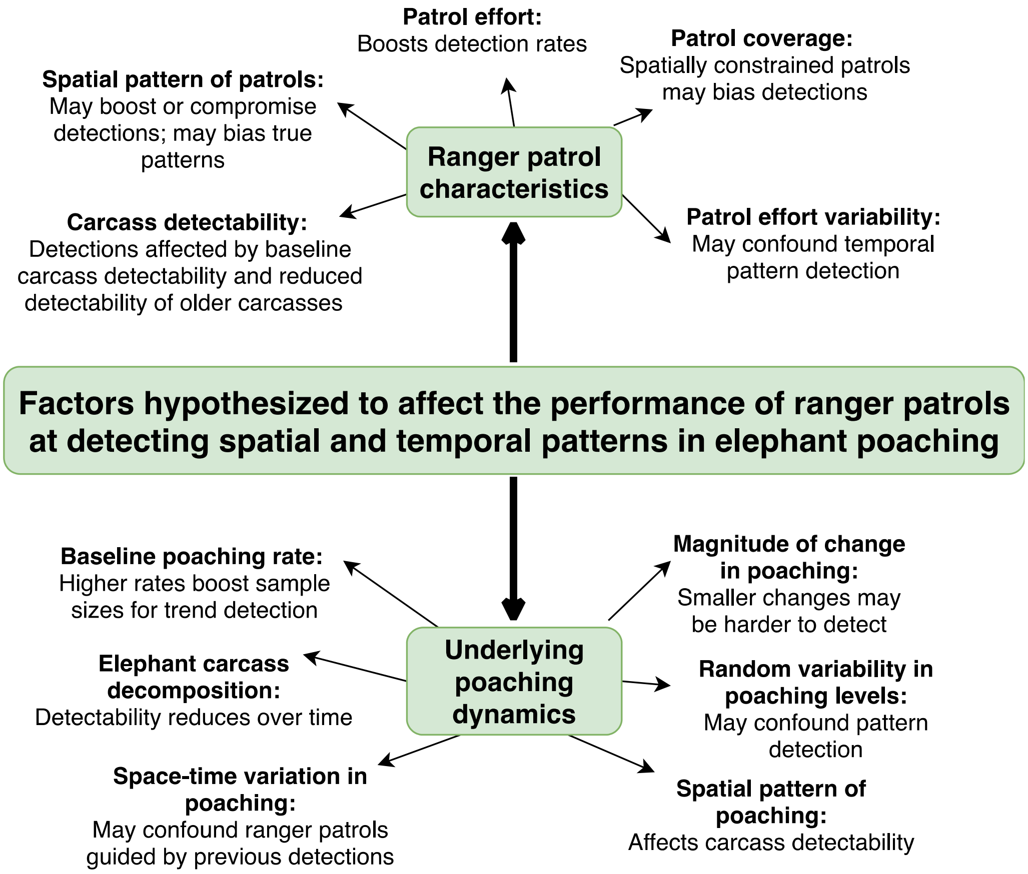



**Figure 4.1.** Various features of ranger patrols and poaching dynamics that I hypothesized would affect the accuracy and precision with which patrols detect underlying spatial and temporal patterns in elephant poaching. Factors were identified using a combination of qualitative knowledge from my field site (see below) and the literature.

*The generic virtual ranger model*

For simplicity, I use the language of ranger-based monitoring of elephant poaching to describe the virtual ranger modelling approach, but the same approach is equally applicable to other contexts where rangers move across time and space collecting data on a process (in this case elephant poaching) which itself varies across time and space. I first constructed a mechanistic elephant poaching sub-model to simulate realistic scenarios of elephant poaching, leading to a defined number and spatial distribution of poached elephant carcasses in the landscape (Fig. 4.2, step 1). Next, I constructed a ranger patrol sub-model to simulate the detection of some of these carcasses by rangers (Fig. 4.2, step 2). I then constructed various scenarios of elephant poaching and ranger patrols (varying key processes such as the poaching rate, the spatial distribution of carcasses, the number of patrols per month, and the spatial pattern of patrols). Finally, I assessed how accurately and precisely the observed data collected by these simulated ranger patrols captured actual poaching patterns (Fig. 4.2, step 3).

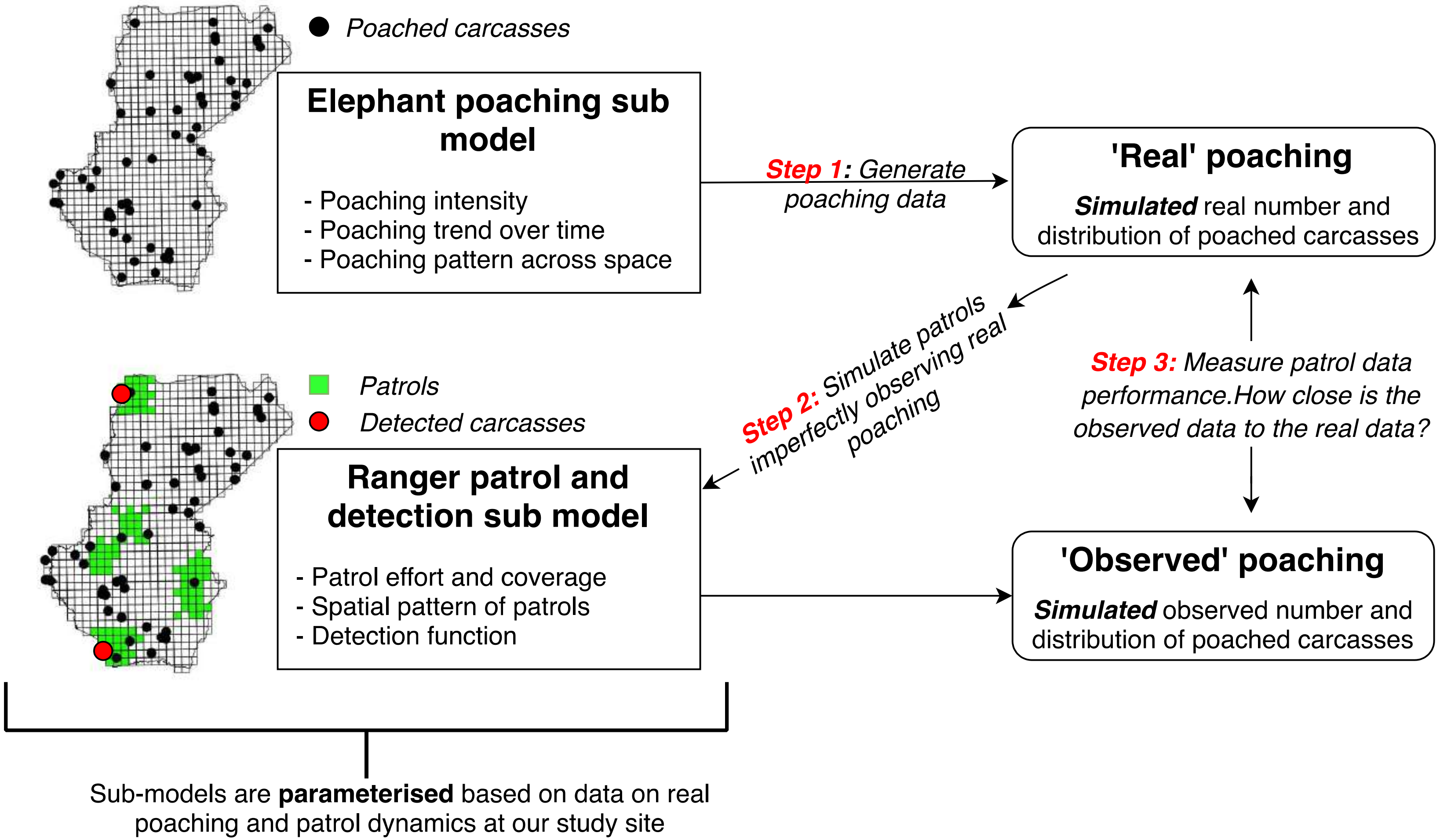



**Figure 4.2**. The virtual ranger approach for evaluating the performance of ranger patrols at capturing spatial and temporal patterns in underlying elephant poaching.

*Study area and model parameterisation*

My case study site is the 3390km$^2$ Chewore Safari Area (hereafter Chewore) in northern Zimbabwe (Fig. 4.3). The elephant population in the broader Zambezi Valley region declined from an estimated 19,981 in 2003 to 11,656 in 2014, mainly due to poaching (ZPWMA, 2015). Chewore is divided into two management units, Chewore North and Chewore South, each with a main ranger station (Fig. 4.3). Since 2000, Chewore has been a designated site under the global programme for MIKE (CITES Secretariat, 2019). Rangers encounter elephant carcasses on regular anti-poaching patrols and record, among other things, the cause of mortality, the animal's sex, its age at death, and estimated time since death.

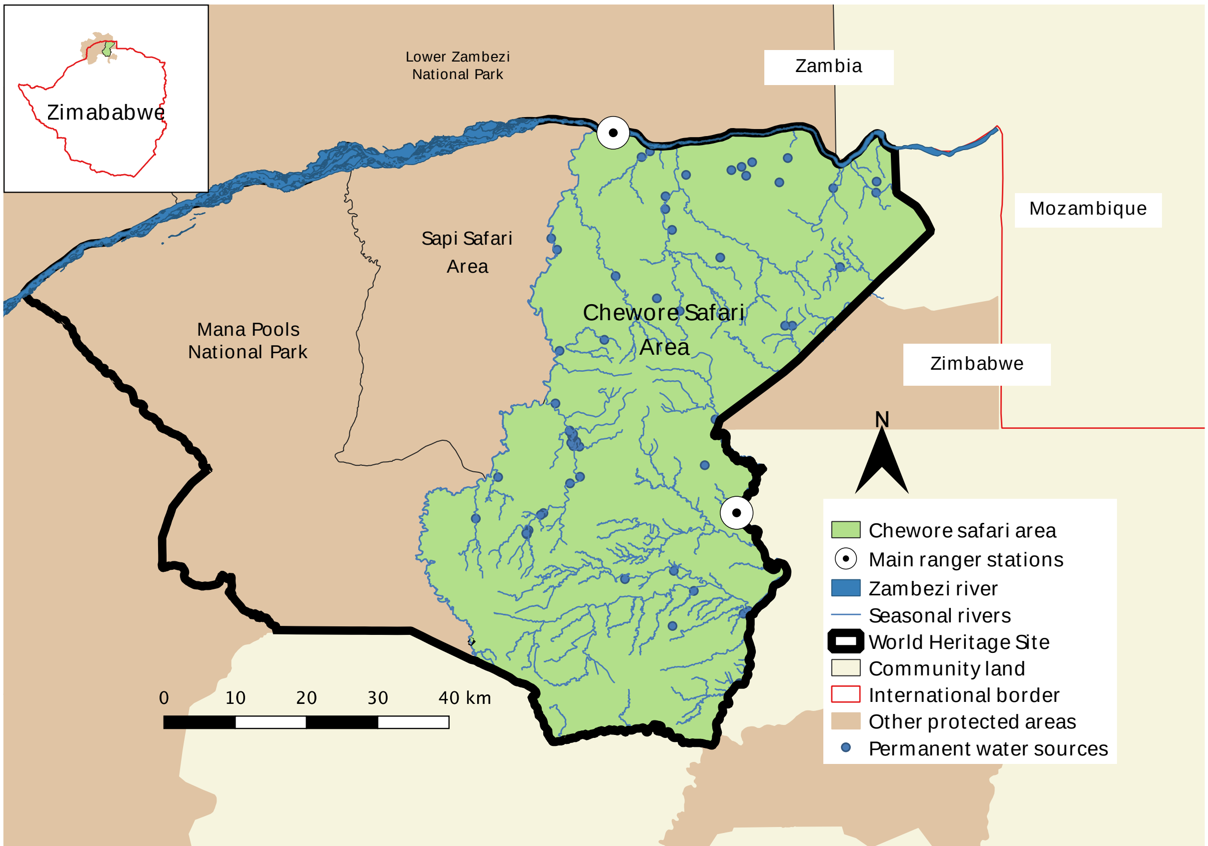



**Figure 4.3.** The Chewore Safari Area in the Zambezi Valley region, Zimbabwe. Quantitative data on real poaching trends, and qualitative interviews with rangers in Chewore were used to parameterise simulations.

I conducted semi-structured interviews with 26 rangers and 10 supervisors at the study site in 2018 and 2019 as part of complementary qualitative work (see Chapters 5 and 6 for details). Interviews provided general information that helped guide model- and scenario-building.

Respondents described current and historic levels of patrol effort, spatial patrol strategy (e.g., the degree to which patrols focus on perceived hotspots of poaching), factors limiting patrol coverage, and seasonal changes in patrolling. Secondly, interviews provided specific information on (a) current ranger patrol characteristics and (b) carcass detections:

a) Each ranger narrated detailed accounts of 1-3 recent patrols (length of patrol, area covered, daily route taken, etc). Rangers indicated routes on a map. A total of 36 independent recent patrol stories were gathered, providing details of how patrols operate at the site, in the absence of reliable geospatial data on actual patrol routes.
b) Each ranger provided details of carcass detections they were involved in and could remember (type of mortality, area, what cues were used to find carcass, etc.). A total of 56 independent detection stories were compiled, where one or more carcasses were detected. This provided essential information on the conditions under which carcasses are found.

In addition to interview data, I accessed a long-term (2000-2017) database on elephant mortality in Chewore. This included details on the cause of mortality, GPS location, age, sex, and estimated time since death for a total of 596 carcasses (201 poached, and 395 natural and management-related mortalities). I also used a raster map of elephant poaching hotspots generated from patrol bias-corrected statistical models that I developed in Chapter 3 (Kuiper et al. 2020).

*Ranger patrols in Chewore*

Routine ranger patrols are regularly conducted across Chewore as part of ongoing monitoring and anti-poaching efforts. The majority of patrols are extended 7-day patrols, with a group of 3-4 rangers deployed by vehicle from one of the two main stations to a particular location for six nights. Rangers set up a temporary camp where they stay for the duration of the patrol, with the aim of monitoring the surrounding area for signs of illegal activity. Each day rangers patrol out in a different direction before moving back to the camp using a different route (resulting in a fan-like patrol pattern radiating out from the camp). The first day is spent patrolling the immediate vicinity of the camp, the last day involves rangers being picked up by vehicle, and one day is typically spent conducting observations from the camp (looking out from a higher point or listening). This leaves four main patrol days, with an average radius moved out from the camp each day of 3-8km (see parameterisation section below). Thus, one 7-day patrol covers a roughly circular area with a typical size of between 28km$^2$ and 201km$^2$

(radius 3-8km). Given that rangers follow defined patrol routes and given the existence of a maximum distance beyond which carcasses will not be detected, the actual square meterage covered will be a fraction of this larger area. For more details on ranger patrol dynamics in Chewore, see Chapter 5.

*Spatial and temporal resolution for virtual ranger model*

I chose spatial and temporal units small enough to adequately represent realistic variation in elephant poaching and ranger patrols and detections across Chewore. I chose a spatial unit of $5km^2$, resulting in a grid of 712 cells across Chewore (Fig. 4.3). This size allowed for adequately fine-scaled modelling of patrol coverage (an average 7-day patrol covers approximately 20 of these $5km^2$ cells) and was also a suitable scale at which to define carcass detectability (see below). The cell size also allowed variation in the underlying poaching intensity across space at a reasonably fine scale (Fig. 4.4). A unit of one month was chosen to reflect the temporal scale at which patrol decisions and deployments are made by management (e.g., a certain number of 7-day patrols are planned each month). It also allowed for stochasticity in poaching rates to be simulated at an appropriate scale. A one-month scale also allowed for an adequate time-series data length for post-hoc evaluation of patrol performance. Finer spatial and temporal scales could have been used, but the trade-off with model complexity and computing time was considered unjustified. Carcass generation and detection were simulated each month, such that the total number of carcasses present in each grid cell in any one month was determined by the number of elephants poached and detected in that cell in previous time steps. Each model scenario was run for 10 years and data from years 5-10 were used for analysis, to allow transient dynamics to run through.

*The elephant poaching sub-model*

I modelled elephant poaching directly using a simple carcass-generating model. The number of carcasses generated each month was determined by the annual poaching rate and multiplied by the elephant population size. The poaching rate was treated as a model parameter and set to 1% or 3% of all individuals, to represent the likely range at Mana-Chewore (see scenarios below). Given that the focus of this analysis is the assessment of patrol performance under different scenarios, I was interested only in changing poaching intensity across space and time, rather than modelling elephant population dynamics (age and sex structure, response to harvest, etc.). Therefore, I used a fixed population size and varied the poaching rate over time according to the poaching trend in each scenario. Generated carcasses were then distributed spatially - the number of carcasses generated each month in each of Chewore's 712 grid cells ($N_p$) was computed as a negative binomial random variable:

$$N_p \sim \textit{Negative Binomial}(\mu\,,\,k)$$

The mean number of carcasses per cell ($\mu$) was determined by the number of carcasses generated per month, divided by 712 (the number of cells). The aggregation parameter ($k$) determined how clustered carcasses were in space. The negative binomial distribution is commonly used in ecology to describe the aggregation of individuals across space, with a single parameter mediating the level of aggregation (Nuno et al., 2013). Lower $k$ values result in 'hotspots' of carcasses, while higher values resulted in a more uniform distribution. To ensure simulations represented realistic spatial patterns in poaching, I parameterised $k$ using the predictions of previously developed ensemble spatial distribution models of poaching across Chewore, based on 17 years (2000-2017) of ranger-collected data on actual poaching incidents (Kuiper et al., 2020). These models, presented in Chapter 3 of this Thesis, used patrol bias correction and participatory modelling to produce robust raster maps of poaching intensity across space. Parameterisation involved two stages: first, $k$ was determined from the shape of the frequency distribution (histogram) of poaching intensity scores. Next, the per-cell realisations of the negative binomial distribution were probabilistically assigned to grid cells based on their poaching intensity score. Grid cells with a higher intensity score were more likely to be assigned the higher realisations of the negative binomial distribution (i.e., to receive more poached carcasses). To illustrate, Figure 4.4 shows the simulated distribution of 100 poached carcasses and the underlying raster map of poaching intensity.

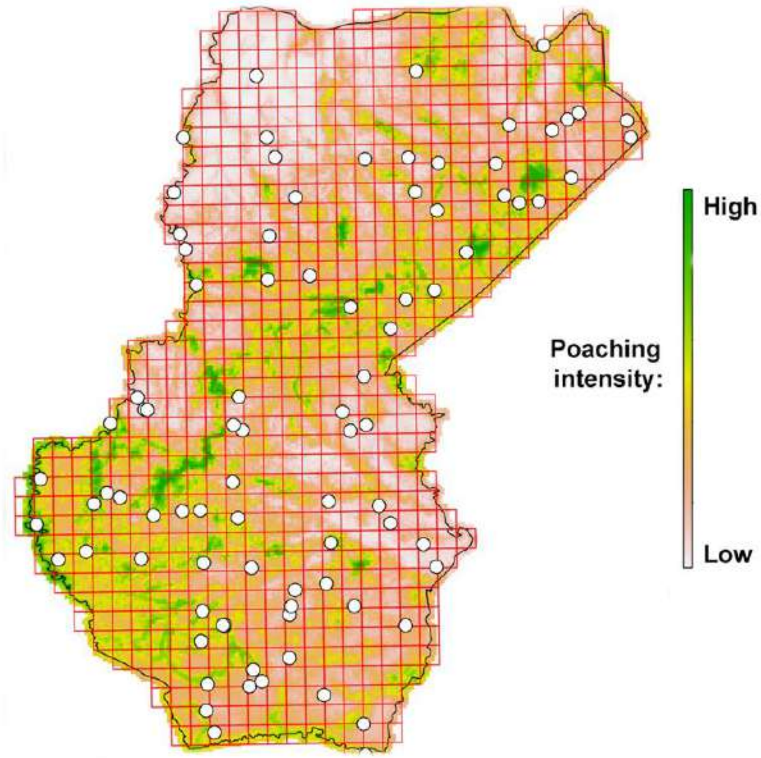



**Figure 4.4**. A simulated distribution of poached elephant carcasses (white dots, n=100) across the 712 grid cells of Chewore, overlaid onto the raster map of poaching intensity that was used to parameterize the simulation. The raster map was developed from actual poaching data (see Kuiper et al., 2020 - Chapter 3 of this Thesis). Within individual grid cells, dots are plotted randomly to aide visualisation.

*Simulating space-time variation in poaching: hotspot locations changing through time*

Poaching data from Chewore suggest that the spatial distribution of poaching changes over time (i.e., there is space-time dependence in the data), so I sought to construct separate simulation scenarios with such dependence built in. This was achieved by representing poaching intensity as a point process (Baddeley et al., 2015) using the R package ‘splancs’ (Rowlingson et al., 2013). I generated separate kernel density maps from actual poaching data for 10 different 6-month periods between July 2010 and June 2015 (Fig. 4.5). Only carcasses for which the date of poaching could be determined with reasonable reliability (i.e., those marked as ‘fresh’ or recent’ by rangers) were used (n=96). After examining results from shorter and longer periods, a 6-month period was chosen as it ensured sufficient underlying data (i.e., enough poaching incidents in each period), while also representing real changes in poaching across periods (Fig. 4.5). Data were too sparse to produce patrol-bias corrected maps for each 6-month period but are likely to represent the broad space-time variation in true poaching. Finally, the same parameterisation procedures as described above (see Fig. 4.4) were used within the model to assign poaching incidents to cells based on poaching intensity scores. Every 6 months, the model cycled through each of the 10 intensity maps presented in Figure 4.5. The data in Figure 4.5 were used only in the scenarios with simulated changing hotspots, otherwise the poaching intensity map in Figure 4.4 was used to parameterise simulations.

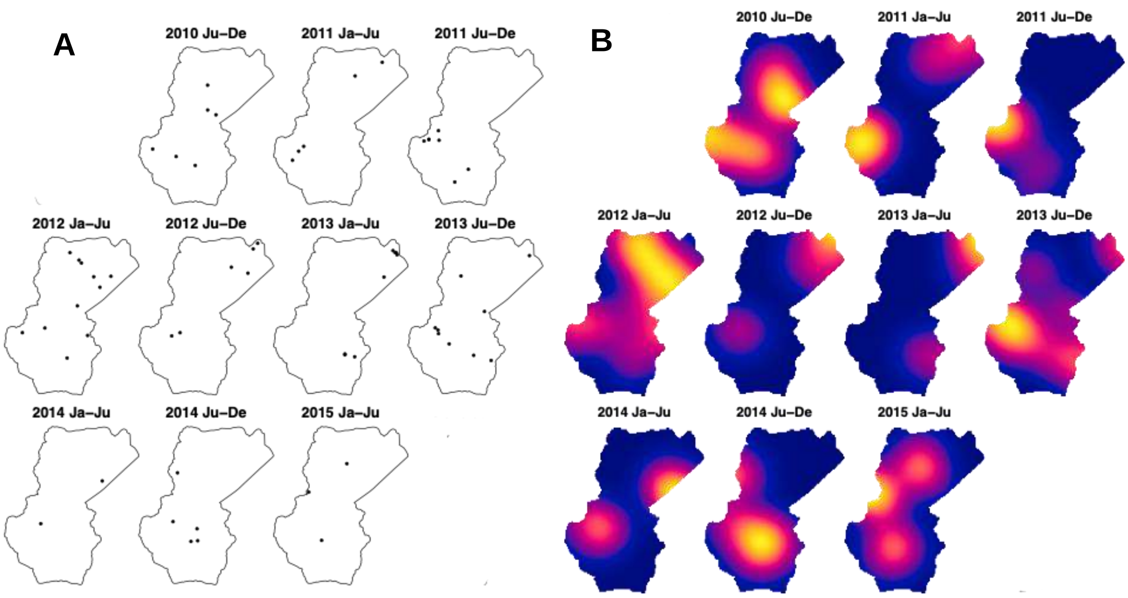



**Figure 4.5.** (A) Changes in the spatial location of real (empirical) poaching incidents in Chewore for 6-month periods between 2010 and 2015. (B) Kernel density plots representing the intensity of the estimated point process that generated the observed poaching pattern. Colour pixels represent density of points per unit area and range from low (blue), through pink (medium), to high (yellow).

*The ranger patrol sub-model*

Each month, a set number of 7-day extended patrols were simulated based on a qualitative understanding of patrol deployment practices (see "*Ranger patrols in Chewore*" above, as well as Chapter 5). Each 7-day patrol was first assigned to a single 5km$^2$ grid cell to represent the location of the central temporary camp from which the patrol was conducted, and then 15-25 surrounding cells were sampled to represent a total area of 75-100km$^2$ covered over the 7-day patrol (the average coverage estimated for patrols in Chewore above; Fig. 4.6). Cells for patrolling were sampled iteratively from adjacent cells (without replacement), with a higher probability of sampling cells closer to the temporary camp. Details of the approach used are included in the model code (see Thesis Appendix 1).

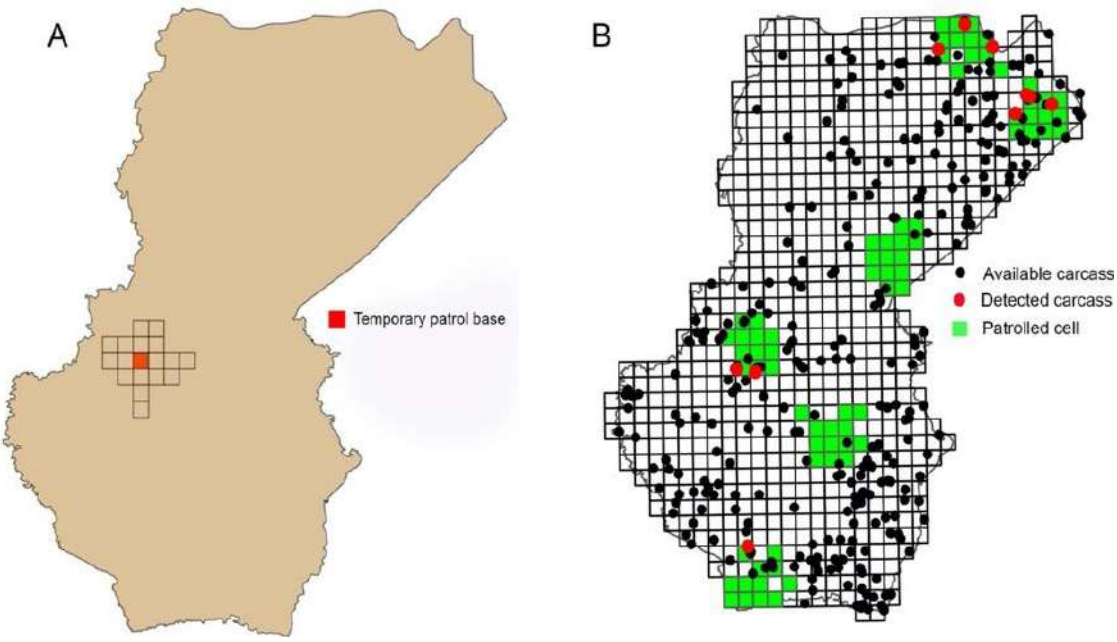



**Figure 4.6.** (A) Simulating the coverage of a single 7-day patrol from a central temporary base. (B) A representative scenario of six individual patrols in a particular month, showing patrol coverage, and poached carcasses available and detected in that particular month (this is from the 5th year of a scenario with an average of seven elephants poached a month; most available carcasses are old and therefore have very low detectability – see main text).

I modelled the number of carcasses detected by a patrol in a particular cell, $N_d$, as a binomial function of the number of carcasses available in the cell ($N_p$; determined by the elephant poaching sub-model), and the baseline carcass detection probability ($D_p$; defined below):

$$N_d \sim Binomial\ (N_p\ ,\ D_p)$$

This random variable allowed for realistic variation in the number of carcasses detected: patrols operating in the same 5km$^2$ cell, with the same number and age of actual carcasses available, may nevertheless detect differing numbers of carcasses, with detections varying randomly around a mean. The random variable thus indirectly captures some of the variation due to the particular direction taken through the grid cell, and the sinuosity of the route followed. Importantly, freshly poached carcasses were assigned a higher detectability than older carcasses (see the next section). Patrol effort was varied directly as the number of 7-day patrols carried out each month. I tested a number of different scenarios for the spatial patterning of patrols among grid cells:

a) *Random patrols*: the central temporary patrol camp is assigned randomly for each patrol.
b) *Targeted patrols*: rangers are more likely to patrol areas where they have detected carcasses before. Grid cells with a higher number of carcasses detected in previous time steps are more likely to be selected as the central patrol camp. The number of previous time steps over which earlier detections are 'remembered' is treated as a parameter variable called 'memory length'.
c) *50% random and 50% targeted patrols*: rangers employ a combined approach of spending half their patrols targeting perceived poaching hotspots and half their patrols randomly exploring new areas.
d) *Constrained patrols:* patrols are more likely in areas closer to the main ranger stations. Interviews indicate that, at certain times, vehicle and fuel limitations constrain patrols to areas nearer the main ranger stations (Fig. 4.3). I used a simple half-normal probability function to assign lower probabilities of patrolling to grid cells further from these stations (Fig. 4.S1; supplementary material is included at the end of this Chapter). Constrained patrols could either be random or targeted.

For patrols that were both constrained and targeted, I calculated relative probability of a patrols in each cell by multiplying the probability based on previous detections by the probability based on distance to ranger station.

I decided not to explicitly test and present results on the effect of patrol effort changing over time because data from Chewore suggest that monthly patrol effort is fairly consistent within years. Also, I ran various test simulations in which I varied patrol effort randomly through time and found little effect on temporal trend detection performance.

*Modelling reduced detectability of older carcasses*

Interview data suggest that fresher carcasses are markedly easier for rangers to detect due to various cues such as gunshots, poachers' foot spoor, vultures circling above the carcass, and smell. As carcasses age, these cues disappear, and they become more difficult to detect. Data on the age of carcasses detected in Chewore confirm that fresh carcasses are more commonly detected than older carcasses (Figure 4.7A).

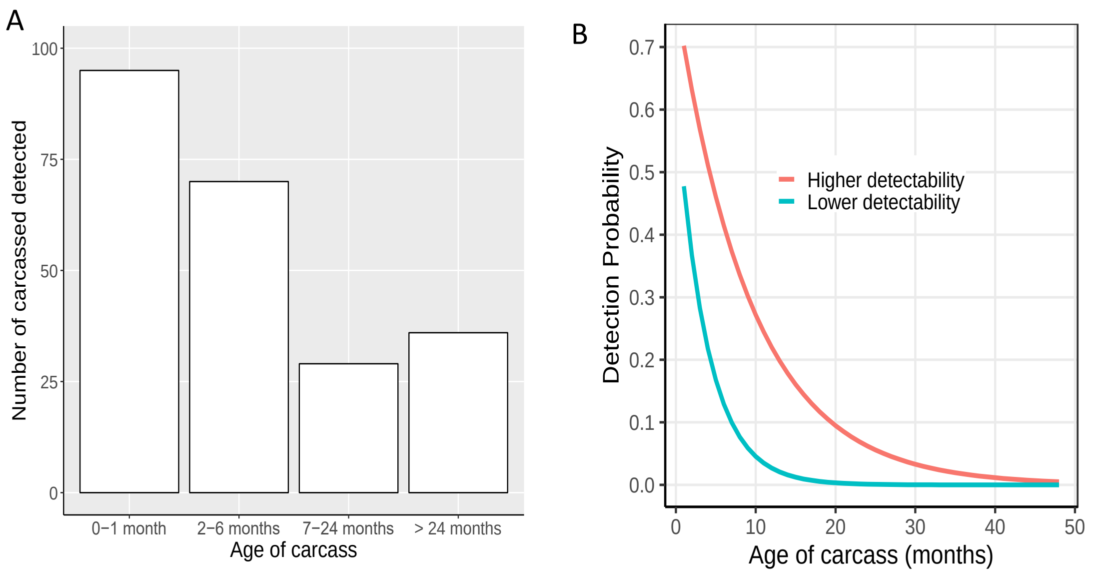



**Figure 4.7.** (A) The estimated age at detection for 195 poached elephant carcasses detected in Chewore between 2000 and 2017. Categories represent those used by rangers to estimate carcass age in the field. (B) The parameterised exponential decay function relating carcass detectability to age, when assuming a higher (70%; red line) and lower (50%; blue line) baseline detectability of fresh carcasses.

Age categories and estimated boundaries represent those used by rangers to estimate carcass age in the field (fresh, recent, old, very old). The decline in detectability of carcasses with age is likely to be steeper than Figure 4.7A suggests because the three older categories have wider age brackets compared to the 1-month bracket for fresh carcasses, and thus greater numbers of carcasses will have been generated and remained undetected from several months of poaching. For example, even if 70% of all newly poached carcasses are detected within 1 month of poaching, the undetected 30% will accumulate for 5 months in the 2-6-month category. In order to simulate these effects within the virtual ranger models, I weighted the data in Figure 4.7A by the length of the age bracket in months to calculate relative differences in estimated detectability for each age category. I then conservatively assumed a baseline detectability of freshly poached carcasses of 70% (i.e., a patrol in a 5km$^2$ grid cell would detect a carcass poached in the same month as the patrol with a probability of 0.7). This 70% value is based on ranger descriptions of carcass detections (see above). Then, starting with this assumed baseline detectability, I fitted an exponential decay function to these relative difference data (Figure 4.7B). Total carcass detections were sensitive to this baseline detectability and resultant detection-age function, so I created a scenario with a reduced baseline detectability of 50% to test the effects on trend detection performance (Figure 4.7B). A Leslie matrix formulation was used to model the number of carcasses available in each of 48 one-month age classes (Caswell, 2001). For each month, the number of carcasses available in each age class, in each cell, was the number of carcasses of the immediate younger age class that were available in the previous month, minus the number detected in that age class in the previous month. Then, based on the parameterised value, carcasses of different ages were assigned a different detection probability value in the binomial detection function (Figure 4.7B). Following the relationship in Figure 4.7B, carcasses "disappear" after 4 years (in the sense of no longer being detectable).

*Designing model scenarios to address key questions and test model sensitivity*

The virtual ranger model developed here is able to test hundreds of parameter combinations (with variations in baseline poaching levels, trends in poaching over time, spatial patterns in poaching through time, patrol effort, patrol pattern, and detection probabilities). However, rather than simulating all possible combinations of poaching and patrol dynamics, I designed a handful of key scenarios that would provide the most useful insights for park managers. This involved modelling poaching and patrolling scenarios that were realistic for Chewore (though I also tested random patrols to give context for the performance of more plausible scenarios).

For all scenarios, I simulated six different levels of patrol effort (1, 3, 6, 9, 12, and 15 patrols per month), three different spatial patrol patterns (random, targeted or mixed), and seven different temporal trends in poaching (no change, 25% increase/decrease, 50% increase/decrease, and 75% increase/decrease). Temporal trends were simulated to occur over a 2-year period (see Fig. 4.8). In all scenarios, the aggregation of poaching incidents was parameterised using real carcass data from Chewore (see above). A baseline poaching rate of 3% was used, as well as a baseline detectability of freshly poached carcasses of 70% (see section 2.9). I then designed four 'standard' scenario variations according to patrol coverage and whether or not there was space-time variation in the underlying poaching pattern (i.e., poaching hotspots change over time; see above). These were:

1. The baseline scenario in which poaching hotspots were simulated to remain constant through time, and with no constraints on the coverage of patrols.
2. A scenario in which poaching hotspots were simulated to change through time, and with no constraints on the coverage of patrols.
3. A scenario in which poaching hotspots were simulated to remain constant through time, and with patrols constrained to areas closer to the main ranger stations.

4. A scenario with poaching hotspots changing through time, and with patrols constrained to areas closer to the main ranger stations.

I also tested the effect of three additional key parameters by varying their values from the baseline value, and then comparing the results in each case to the results with the baseline values. These were: (1) The annual poaching rate (testing 1% in addition to the baseline 3% ); (2) The baseline carcass detectability (testing 50% in addition to the baseline 70%; see above); and (3) The period over which the temporal changes in poaching were simulated (testing 1- and 3-year periods in addition to the baseline 2-year period).

*Measuring the performance of ranger patrols under different scenarios*

Note the terms “real” and “detected” poaching are used when presenting data on patrol performance, but it must be noted that all data are simulated and are therefore not real data in the empirical sense. Poaching trends were simulated for defined periods (1-3 years depending on the scenario). For each scenario, temporal trend detection performance was measured as the proportion of simulation replicates in which patrols successfully detected the real trend in poaching (following Jones et al., 2017). For declining trends, a replicate was categorised as achieving successful trend detection if the mean number of poached elephants detected by patrols in the 12 months after the simulated trend was significantly lower than the mean number detected in the 12 months before the trend (and vice-versa for increasing trends, Fig. 4.8). A t-test was used to assess significance, defined as $p<0.10$. I chose not to use a p value of 0.05 because the threshold of required proof is likely lower for a precautionary park manager who does not want to miss any large change in poaching. I considered the t-test method to be closest to what managers might ask in the real world, i.e., ‘are poaching levels this year lower than they were in previous years?’

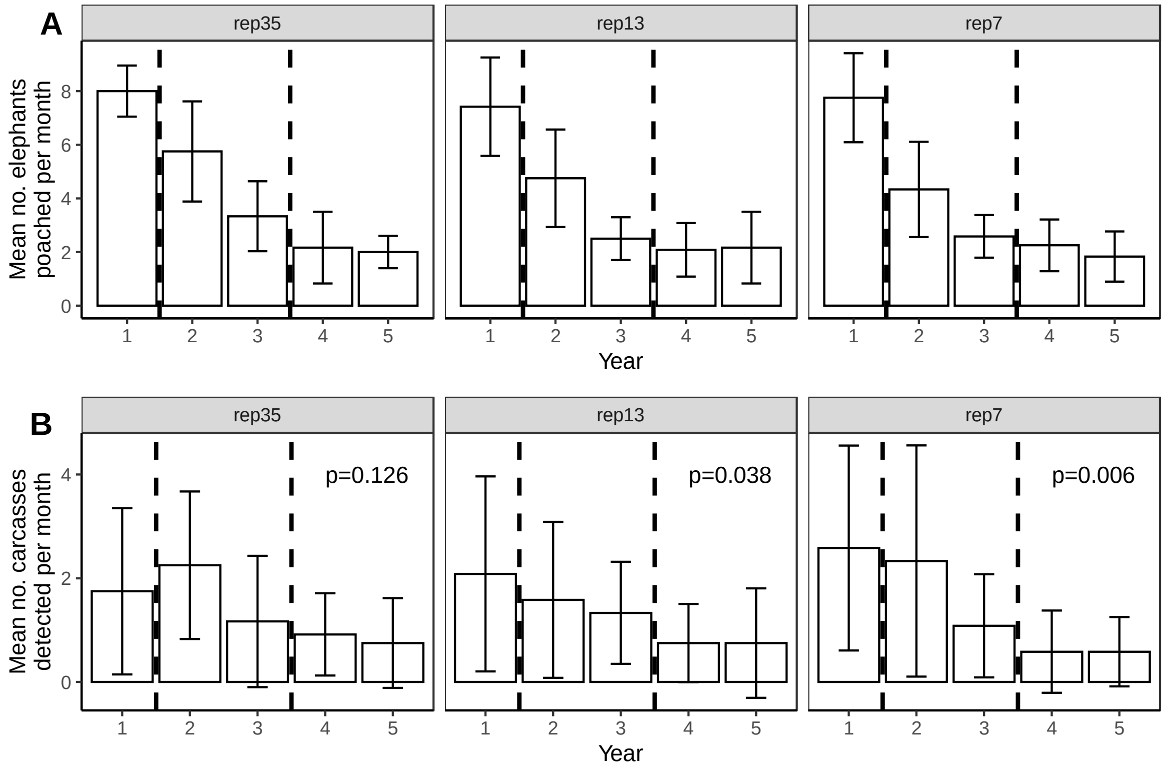



**Figure 4.8.** Calculating power to detect change: (A) The simulated 'real' trend in poaching (75% decline in this example), and (B) The subsequent simulated number of poached carcasses detected by rangers, for three random simulation replicates from a typical model scenario. The simulated trend starts at the start of the second year and ends after 2 years (see dotted lines). Power was determined as the proportion of replicates (n=50) for which the number of poached elephant carcasses detected per month was significantly lower in year 4 versus year 1 (P<0.10). Replicates 13 and 7 would have been classified as successful trend detection in this case. Data are means and standard deviations.

Spatial trend detection performance was measured as the spatial congruence between real and detected poaching in simulation scenarios with no temporal changes in poaching over time. Managers in Mana-Chewore do not identify spatial poaching hotspots at the fine scale of 5km$^2$ used for grid cells in these simulations, neither do they assess hotspots at very large spatial scales. I therefore chose to measure congruence at a management-relevant spatial scale of 45km$^2$ (representing 3x3 clusters of nine 5km$^2$ park grid cells). Congruence was calculated as the Pearson's correlation coefficient between the simulated real number of elephants poached, and the number detected by patrols, for each 45km$^2$ grid cell covering Chewore (Figure 4.9). Overall spatial detection performance was measured using the mean and standard deviation of the correlation coefficient across all simulation replicates in each scenario. Spatial correlation was measured for a three-year period in the middle of the simulation period, to represent an average period of management interest. Results were similar when a 1-year and 2-year period were used. Next, to visually represent how spatial patterns of real poaching differed from observed poaching for different levels of patrol effort, I produced kernel density plots from the real and observed carcass data in each scenario. I used the simple kernel density function in R (*density*) with Gaussian smoothing.

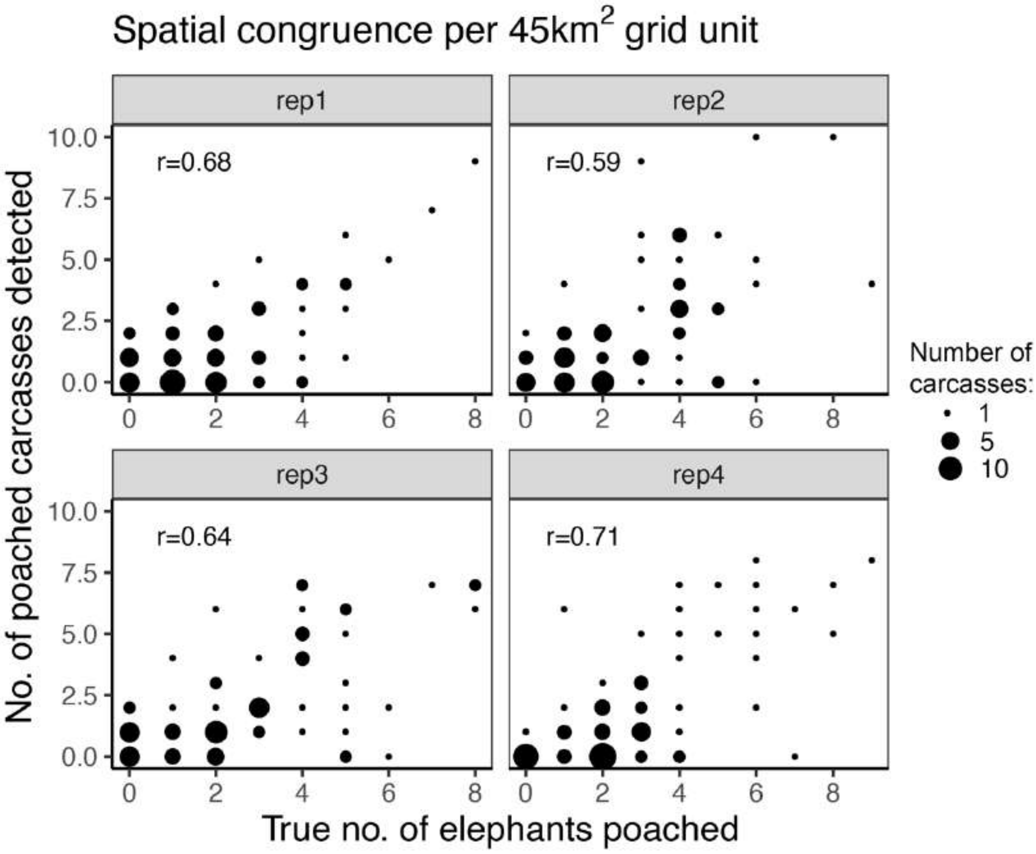



**Figure 4.9**. An illustration of the method used to assess spatial congruence between true and detected poaching. The correlation between the true and detected number of elephants poached in each 45km$^2$ grid unit across Chewore (n=79 units), over a 3-year period in the middle of the simulation period (see main text). Each unit is a cluster of 9 park grid cells. Illustrative data are shown for the baseline scenario with a poaching rate of 3% and 6 spatially random patrols per month, for four of the 50 simulation replicates. It is possible for detected carcass numbers to exceed poached numbers as rangers detect carcasses poached outside of the 3-year correlation period.

## 4.3. Results

*The effects of patrol effort, coverage and pattern on the power to detect temporal changes in poaching*

In all scenarios, the proportion of poached carcasses detected by ranger patrols approximately doubled when effort was increased from 3 to 9 patrols/month and doubled again when effort was increased to 15 patrols/month (Fig. 4.10). Targeted patrols tended to detect a lower proportion of carcasses than random or mixed patrols (5-25% less depending on the scenario). The best patrol performances were achieved when poaching hotspots were consistent through time and patrols were unconstrained (scenario 1, Fig. 4.10). When poaching hotspots were simulated to change through time, overall detections of targeted patrols relative to random and mixed patrols declined slightly (scenarios 2 & 4), while spatial constraints on patrols (patrols limited to areas nearer the ranger bases) markedly reduced overall detections (scenarios 3 & 4).

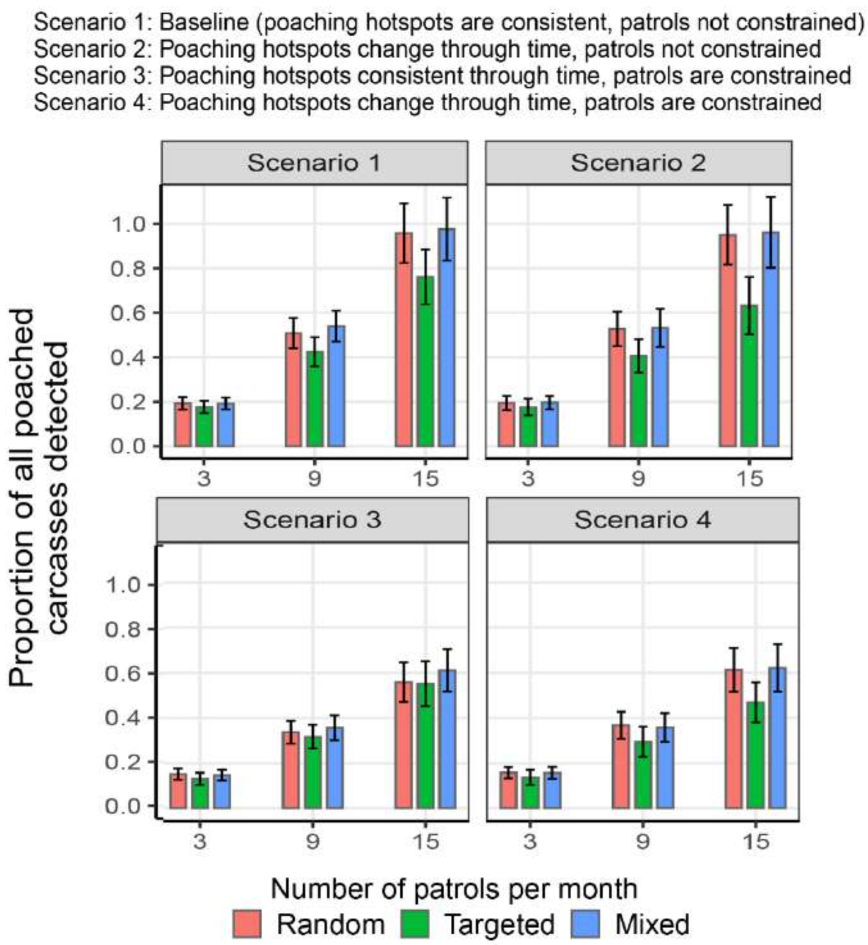



**Figure 4.10**. The effect of various patrol characteristics on the mean number of carcasses detected by ranger patrols across years, as a proportion of all poached elephant carcasses 'available' (undetected or newly poached) in Chewore each year. Data are shown for the scenario with no temporal change in poaching intensity over the simulation period. Patrol characteristics include effort (patrols per month), spatial patrol pattern (random, targeted to areas of high previous detections, or a 1:1 mix of the two), and patrol coverage (constrained to areas near the main ranger stations or not). The effect of space-time variation in poaching (where the locations of poaching hotspots change over time) is also shown.

Across all scenarios, the spatial pattern of patrols (random versus targeted to areas of high previous detections) had no noticeable effect on the power to detect temporal trends in poaching of different magnitudes (Fig. 4.11; supplementary material Fig. 4.S2). At a 25% simulated change in poaching, the power to detect change was around 20% whether it was an increase or a decrease (Fig. 4.11). While at 75% change, the decrease was almost 100% detectable, while the increase was both less detectable and increased slightly with patrol effort (from about 0.7 to 0.85). Only at intermediate change (50% change) did the patrol effort make a major difference, and then more for a decrease in poaching than an increase - where the power increased by 50% from about 10% at 1 patrol a month, to about 65% at 15 patrols per month (Fig. 4.11).

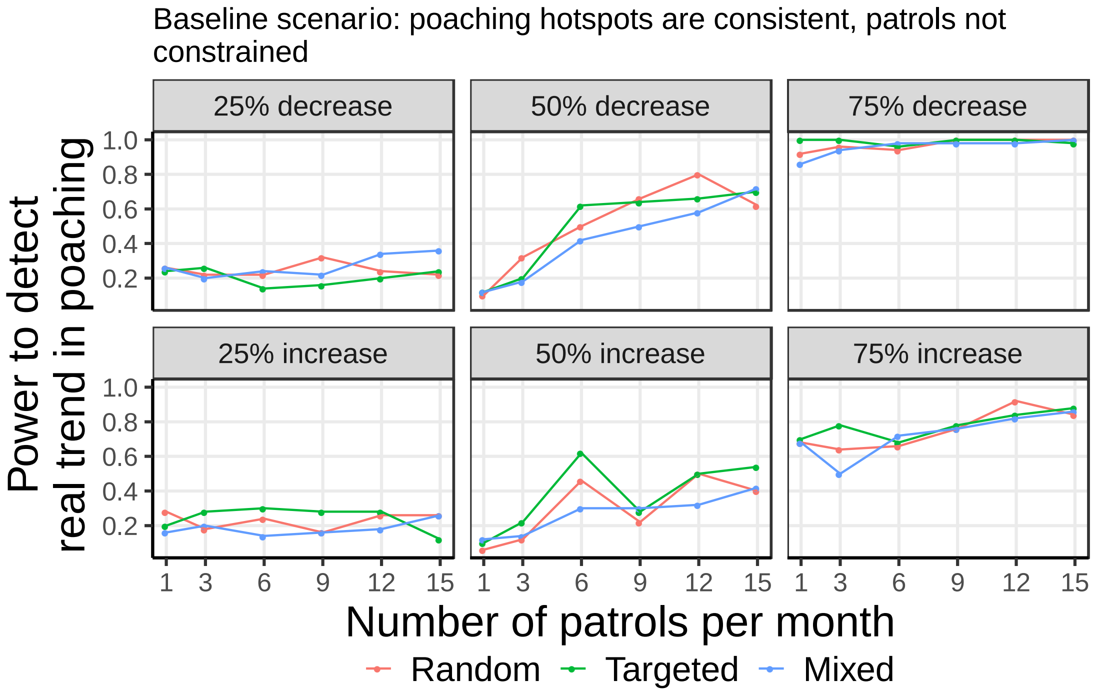



Figure 4.11. The effect of patrol effort on the power of ranger-collected data to detect temporal trends in elephant poaching of different magnitudes, in the baseline scenario. Trends were simulated to occur over 24 time-steps (representing a 2-year period), from a baseline poaching rate of 90 elephants p.a. (3% of the population). Power is measured as the proportion of simulation replicates for which a statistically significant change in ranger-detected carcasses was observed in the year before versus the year after the trend in poaching (see methods).

Compared to the baseline scenario with consistent poaching hotspots, changes in the locations of underlying poaching hotspots led to only slight, non-significant changes in the power to detect change, even for targeted patrols (Fig. 4.12: “Changing hotspots”). The constraint of patrol coverage to areas closer to the main ranger stations had a slightly larger effect on the power to detect changes in poaching, with high variability in power for temporal changes of 50% (Fig. 4.12: “Constrained patrols”). A combination of changing poaching hotspots and constrained patrol coverage had a more notable effect on power to detect change, particularly for increasing trends in poaching (Fig. 4.12: “Both”). This discrepancy between increases and decreases is discussed more below (Fig. 4.13).

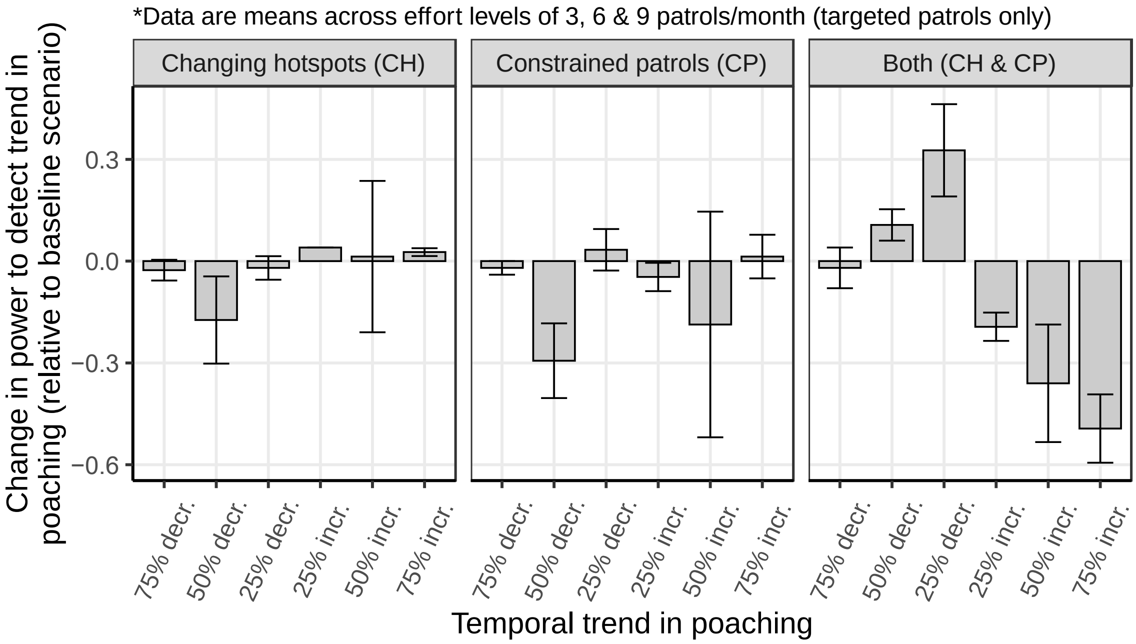



**Figure 4.12.** The effect of changing poaching hotspots, and constraints on patrol coverage, on the power of patrols to detect temporal changes in poaching of different magnitudes. Data represent mean changes (across three average levels of patrol effort: 3,6 and 9 patrols/month) in power to detect temporal changes in poaching in each scenario relative to the baseline scenario. The baseline scenario has consistent poaching hotspots and no constraints on patrols. Only data for targeted patrols are shown (results were similar for random and mixed patrols).

Increasing trends in poaching were generally less detectable than decreasing trends of the same magnitude, particularly in scenarios with poaching hotspots changing over time and/or constrained patrols (Fig. 4.13). Similar to previous trend detection results, differences were most noticeable for 50% changes in poaching in the baseline scenario. In this scenario, 50% increases in poaching were detectable with only a third to half of the power with which 50% decreases were detectable (Fig. 4.13 “Baseline”). When both changes in poaching hotspots and constrained patrols were simulated, increases in poaching were detectable with only a small fraction of the power of decreases in poaching, regardless of the spatial pattern of patrols (Fig. 4.13 “Baseline”).

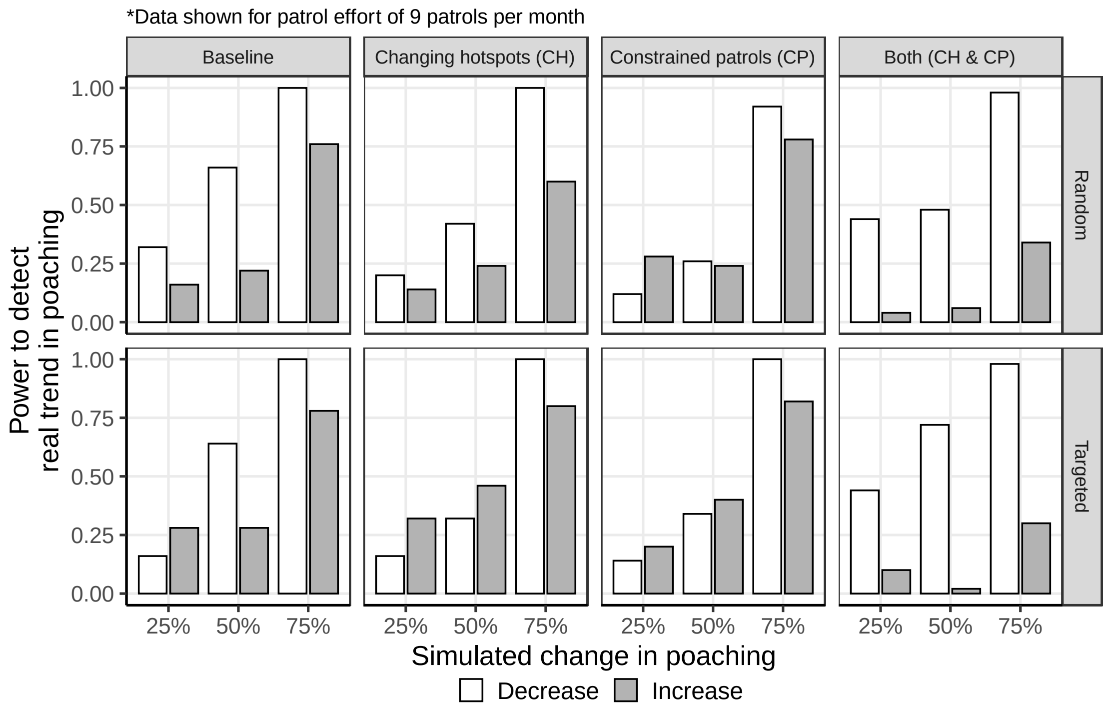



**Figure 4.13**. Differences in the power of ranger patrols to detect increasing versus decreasing temporal trends in elephant poaching, for different patrol types and scenarios. Data are shown only for a patrol effort of 9 patrols per month (the approximate current effort level in Chewore).

Unlike the Type 2 error rate (1-power), which was variable depending on the scenario in question, the Type 1 error rate (detecting a trend when there was none) was consistently low (around 20%) in most scenarios. (supplementary material Fig. 4.S3). Type 1 error rates were highest when patrols were targeted to areas of high previous detections, especially in scenarios where poaching hotspots changed over time (Fig. 4.S6). This is likely to be because targeted patrolling is more 'hit and miss' compared to random patrols and may thus result in increases or decreases in detections over time, independent of the temporal trend in poaching. Changes occurring over both shorter (1-year) and longer (3-year) periods were detectable with similar power to the changes over a 2-year period in most scenarios (supplementary material Fig. 4.S4). However, simulated 3-year trends in poaching were markedly more detectable than 1 and 2-year trends for larger increases in poaching (50% and 75%) in the scenario with both changing poaching hotspots and constrained patrols (Fig. 4.S4).

*The effect of patrol effort, patrol pattern, and patrol coverage on the spatial correlation between real and detected poaching*

In the baseline scenario, there was a large increase in the spatial congruence between real and ranger-detected poaching with increasing patrol effort (Fig. 4.14). The rate of increase in spatial congruence with patrol effort tended to be highest for lower effort levels, with congruence increasing by about 50% (0.45 to 0.65) between 3 and 9 patrols per month but only by another 15% (0.65 to 0.75) between 9 and 15 patrols/month (Fig. 4.14). The variability in spatial congruence also declined with effort. The spatial pattern of patrols did not affect how closely spatial patterns in detected poaching matched real poaching, with random, targeted and mixed patrols performing very similarly in all scenarios. These patterns held true for the changing hotspot and constrained patrol scenarios (supplementary material Fig. 4.S5).

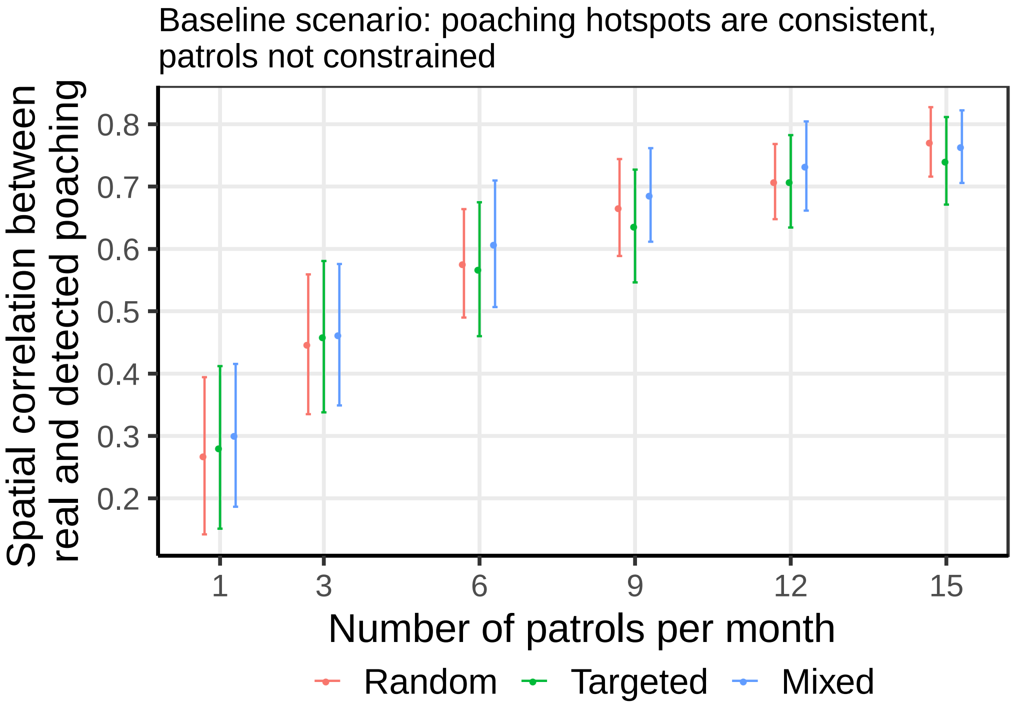



**Figure 4.14.** The spatial congruence between real and detected poaching (means and standard deviations across 50 simulation replicates). The effect of patrol effort and patrol type (spatially random, targeted to areas of previous detections, or mixed) on the spatial correlation between the real number of elephants poached and the number of poached elephant carcasses detected in each of 79 45km$^2$ grid units across Chewore's. Simulated poaching intensity was constant at 3% (90 elephants per year) and correlation was determined for a 3-year period in the middle of the simulation period (see methods).

Visual comparisons of underlying poaching intensity and that inferred from ranger patrols suggest that spatially random and spatially targeted patrols performed similarly in terms of capturing spatial patterns of poaching (Fig. 4.15).

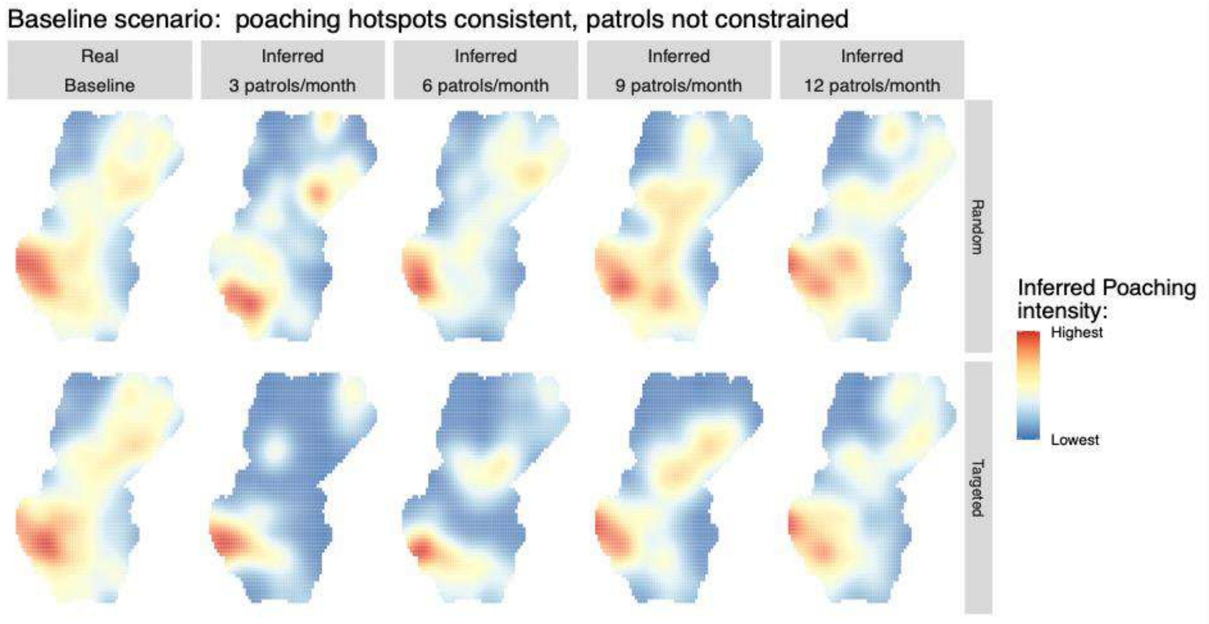



**Figure 4.15**. A visual representation of the simulated underlying poaching intensity ("Real Baseline") and how closely the poaching intensity as inferred from ranger-collected data ("Inferred") matches this baseline, for different levels of patrol effort and patrol types (spatial random or targeted to areas of high previous detections). Data are shown for only a single simulation replicate at each effort level and for each patrol type (results were however similar for several other visualised replicates). Poaching intensity values represent kernel density estimates generated from the underlying distribution of simulated real and detected poaching (see methods).

The constraint of patrols to areas closer to the main ranger stations led to a notable decline in the spatial congruence between real and detected poaching (Fig. 4.16). Spatial congruence between real and detected poaching increased slightly when poaching hotspots changed over time, even when patrols were targeted to areas of high previous detections (Fig. 4.16). This was surprising as one would expect spatial targeting to lead to biased results, because past carcass locations (the information used by patrols to target future patrols) would not be a good predictor of future carcass locations when poaching hotspots change over time. The fact that targeted patrols performed similarly to random patrols in temporal trend detection was also surprising. I hypothesised that these unexpected results may be because poaching in Chewore is not sufficiently spatially clustered to lead to 'bad learning' through targeted patrols (Fig. 4.17). This explanation was borne out in that, when the level of aggregation of underlying poaching incidents was simulated to be significantly higher than that observed in Chewore, targeted patrols became significantly less effective (relative to random patrols) in the scenario with poaching hotspots changing through time (Fig. 4.17). This suggests that targeted patrols do not strongly bias inferred spatial or temporal patterns in poaching in contexts where poaching is not highly clustered (as in Chewore).

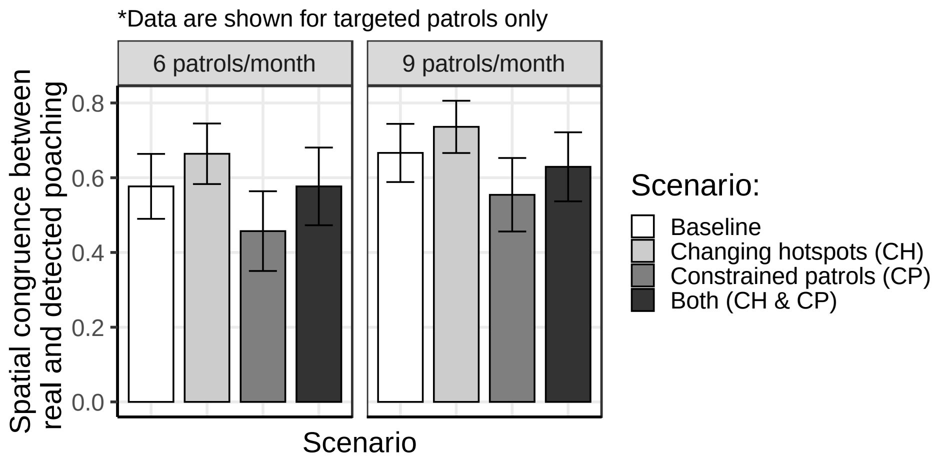



**Figure 4.16.** Differences among scenarios in the spatial congruence between real and detected poaching, showing the effect of constrained patrol coverage and changes in underlying poaching hotspots over time (means and standard deviations across 50 simulation replicates). Data are shown for the represent. Only data for spatially targeted patrols are shown (results were very similar for random and mixed patrols).

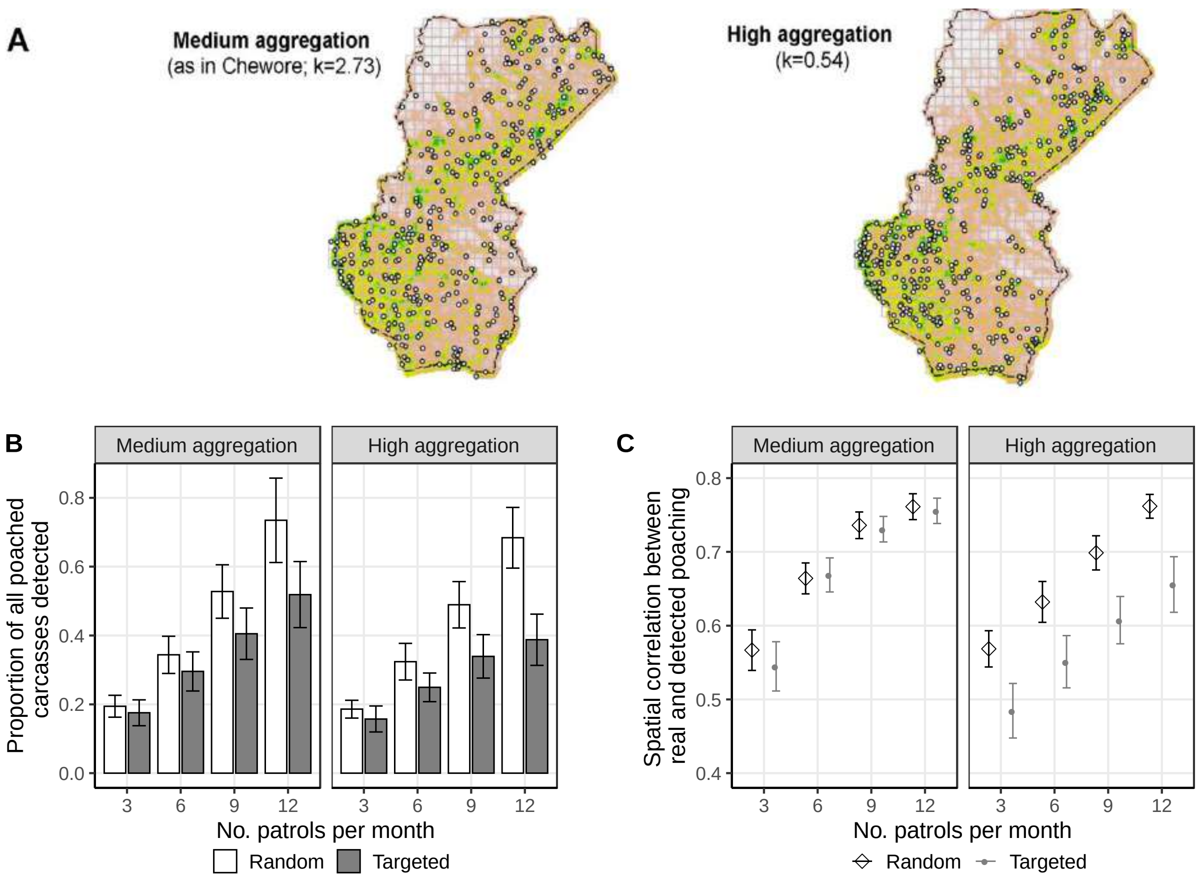



**Figure 4.17.** Testing the effect of the simulated aggregation of poached carcasses on the relative performance of targeted and random patrols at capturing spatial patterns in poaching when poaching hotspots are simulated to change through time. (A) Simulating different aggregation levels by varying *k* in the negative binomial model used to set the carcass distribution (see methods ). A distribution of 300 carcasses is shown for illustration. (B) Overall carcass detections (means per year across replicates) for targeted and random patrols. (C) Spatial congruence between real and detected poaching measures as Pearson correlation across 80 grid units of 45km$^2$ (see Methods).

*The effect of poaching intensity on patrol detection performance*

When the baseline poaching rate was reduced from 3% to 1%, patrols tended to detect a lower proportion of the available carcasses, across most scenarios (Fig 18A). The likelihood of patrols detecting temporal changes in poaching reduced significantly when the baseline poaching rate was lower (Fig. 4.18B). Even relatively high levels of effort (9 patrols/month) could not detect large changes in poaching with more than 50% power (Fig. 4.19B). This is likely due to sample size effects: only around 30 elephants (1% of a population of 3000) are poached per year in the 1% scenario (versus 90 per year in the 3% scenario), so a 50% decline would represent a decline from an average of 30 to 15 elephants poached per year (see Fig. 4.19 for an illustration of this effect). In contrast to temporal trend detection, a lower baseline poaching rate had only a small adverse effect on the spatial congruence between real and detected poaching (Fig. 4.18C).

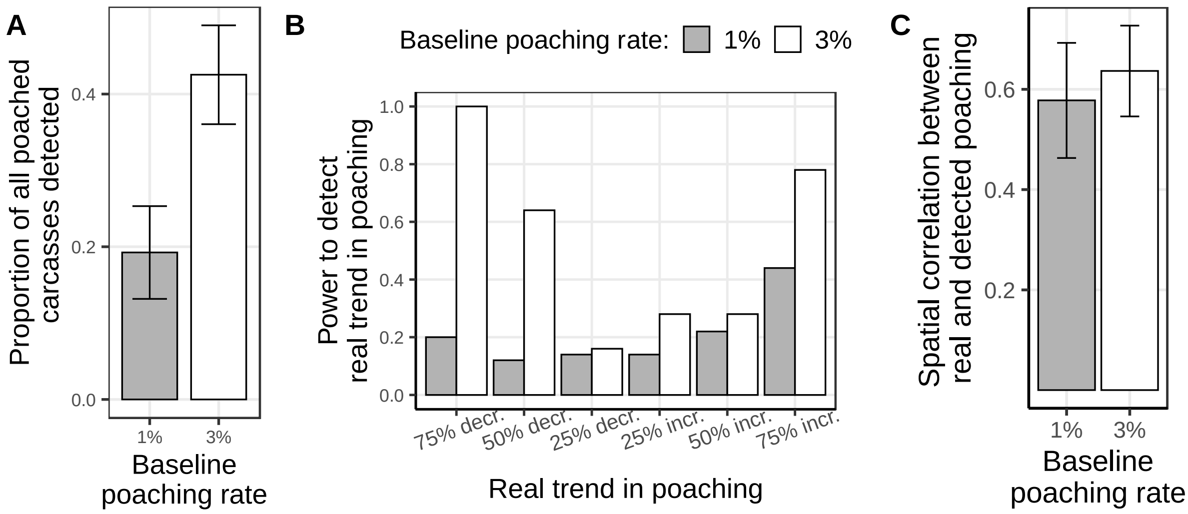



**Figure 4.18**. The effect of the baseline poaching rate on (A) overall carcass detections, and on the performance of ranger patrols at capturing (B) temporal and (C) spatial patterns in poaching. Data are shown for an intermediate level of patrol effort of 9 patrols per month (the closest to the current reality in Chewore), and only for targeted patrols (results for spatially random and mixed patrols were similar).

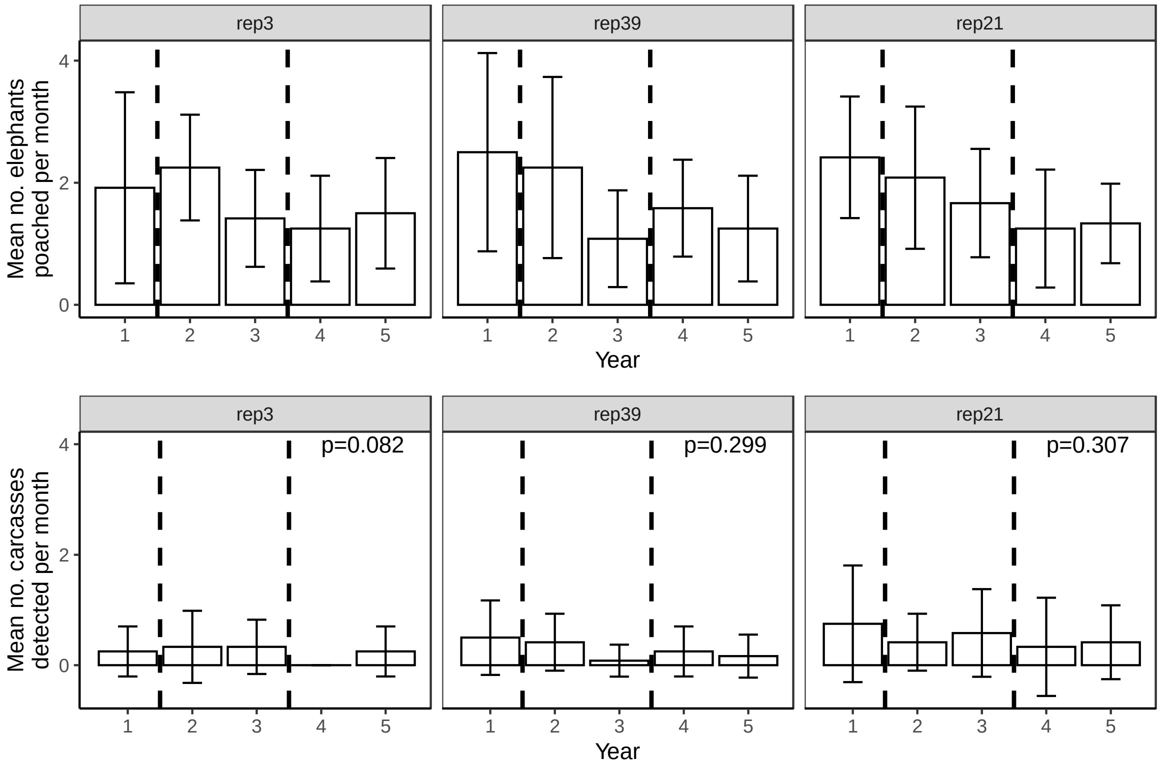



**Figure 4.19.** The effect of small sample sizes in the low poaching scenario on temporal trend detection performance, showing the trend detection calculation for three illustrative replicates (randomly selected) in a representative scenario (50% simulated decline in poaching with baseline poaching of 1%, and 3 patrols per month). Compare with Figure 4.8 (see methods) which shows the same plot for the 3% scenario.

*The effect of reduced carcass detectability on patrol detection performance*

When the simulated baseline detectability of freshly poached carcasses was reduced (see methods for a full explanation), a significantly lower proportion of carcasses was detected (Fig. 4.S6A). Despite this, patrols for which the carcass detectability was lower performed only slightly worse than patrols with higher detectability at detecting temporal changes in poaching (Fig. 4.S6B). However, patrols with lower carcass detectability performed significantly worse at capturing spatial patterns in poaching than patrols in the higher detectability scenario (Fig. 4.S6C).

Table 4.1 presents a summary of all the results presented in this Chapter, showing how various features of ranger patrols and underlying poaching dynamics affect trend detection performance.

**Table 4.1**. A summary of the effect of key features of (a) ranger patrols and (b) poaching dynamics on the performance of patrols at detecting spatial and temporal patterns in poaching. The size of the effect is indicated (none, small, medium, or large), along with details of the overall effect of each feature, across scenarios.

| **Feature** | **Effect on temporal trend detection** | | **Effect on spatial pattern detection** | |
|---|---|---|---|---|
| | Effect | Details | Effect | Details |
| *(A) Ranger patrol characteristics* | | | | |
| Patrol effort | Med. | Only affects the power to detect medium (50%) changes in poaching. | Large | Markedly increases spatial congruence between real and detected poaching. |
| Spatial pattern of patrols | None | Targeted and random patrols achieve very similar power to detect trends. | None | Random and targeted patrols perform very similarly at detecting spatial patterns in poaching. |
| Constrained patrol coverage | Med | Significantly reduces carcass detections and the power of patrols to detect 50% temporal changes in poaching (no effect for 25% and 75%). | Med | Causes small declines in detection performance. Further declines when combined with changing hotspots. |
| Lower carcass detectability | Small | Does not affect detection of small (25%) and large (75%) changes in poaching. Only slightly reduces power to detect medium (50%) changes. | Large | Leads to large declines in performance. Further declines when combined with changing hotspots. |
| *(B) Elephant poaching dynamics* | | | | |
| Reduced poaching rate | Med. | Reduces power to detect medium (50%) and large (75%) temporal changes in poaching, but no effect for small (25%) changes. | Small | Negligible effects. |
| Changing poaching hotspots | Small | Depending on the scenario, zero or only very small effects on the power to detect temporal trends. | None | Does not significantly change spatial pattern detection performance. |
| Direction of trend in poaching | Med | Increases in poaching are less detectable than decreases, particularly when the magnitude of change is medium or large (50% or 75%). | NA | NA (spatial performance is measured for the no trend scenario). |
| Period over which change occurs | Small | Changes in poaching occurring over 1, 2 or 3 yrs were detectable with similar power | NA | NA (spatial performance is measured for the no trend scenario). |

## 4.4. Discussion

Monitoring data are essential to evaluating what does and what does not work in conservation (Sutherland et al., 2004). Yet monitoring programmes may be expensive to implement effectively, and the value of information they provide needs to be carefully considered in the context of limited protected area management budgets (Canessa et al., 2015). In situations where monitoring data are both necessary to effective decision-making and require significant investment to collect, it is imperative that the monitoring design yields enough power to accurately detect trends of management interest at relevant scales. If not, limited conservation funds would be wasted only to provide unreliable information for decision-making. Understanding the factors that drive the accuracy and precision of monitoring data is therefore crucial (Collen and Nicholson, 2014; Field et al., 2007; Legg and Nagy, 2006). In this Chapter I used a simulation modelling approach to explore the power of ranger patrols to detect spatial and temporal patterns in elephant poaching under various patrol strategies and poaching scenarios.

*Begin with the end in mind*

The virtual ranger model developed here provides a useful tool for identifying the patrol strategies necessary to answer focussed management-relevant questions. Too often monitoring programmes are implemented without proper consideration of whether or not they are adequate to address the key management questions for which they were designed (Chee and Wintle, 2010). Indeed, often the management questions are not well articulated beforehand. A critical step in achieving the goal of better integration of monitoring results with conservation management decisions is that management questions are clearly articulated, so that monitoring is designed to provide data that can reliably answer these questions (Ficetola et al., 2017; O'Kelly et al., 2018). This is particularly important in the context of ranger-based monitoring, because observational data from patrols are often seen only as an 'add-on' to the primary law-enforcement element of patrols (Keane et al., 2011).

My results are sobering in that many common management questions relating to spatial or temporal trends in poaching would be difficult to answer well with ranger-collected data in Chewore. Often high levels of patrol effort, wide patrol coverage, and high levels of poaching (leading to higher carcass sample sizes) are required for patrols to accurately capture even short term and relatively extreme spatial and temporal trends in poaching (Table 4.2). In her review of the role of ranger-based monitoring in informing tiger conservation across 8 Asian sites, Stokes (2010) suggests that various biases in patrol pattern and detectability mean that ranger-collected data may not be appropriate to answer questions around long term (>1 year) trends in conservation threats. She suggests such data might be more appropriate as a source of immediate data on the presence/absence of illegal activities so that managers can respond directly to present threats. These intuitive suggestions can be rigorously assessed using a virtual ranger approach as developed here and may be sensitive to the nature of the underlying threat (illegal hunting of tigers in Asia will be different from elephant poaching in Zimbabwe). In either case, it is crucial that the use for which ranger-based monitoring data is intended, and the particular questions that managers or ecologists hope to answer from the data, are clear.

For monitoring more generally, various other factors will affect whether collected data are suitable to answer the particular question of interest. In her case study of species and threat monitoring in Madagascar, for example, Earle (2016) found that the monitoring programme lacked power to detect trends, but could provide reliable information of the presence or absence of species and threats. Similarly, in her study of local knowledge for wildlife monitoring in Cameroon, Brittain (2019) found that power to detect trends in populations of particular forest species depended on the method of sampling, the characteristics of the observer, and the particular species in question. These examples again illustrate the importance of defining the goal of the monitoring programme *a priori*, and being specific about what species, which threats, and what trends are important.

*Using ranger-collected data to capture temporal trends in poaching*

The ability of patrol effort to detect temporal patterns in poaching depended strongly on the magnitude of the underlying trend in poaching. Even very high effort (more than 15 seven-day patrols/month) was not sufficient to detect small (25%) declines and increases in poaching, while large (75%) declines/increases were detectable with very low effort (1-2 patrols per month). The significant management relevance of this is that small and large changes in poaching are likely to be either virtually undetectable or confidently detectable (respectively) regardless of patrol effort. Therefore, decisions about allocations of budget to patrol effort are more important in the context of detecting intermediate changes in poaching levels (50% over 2 years).

**Table 4.2**. The patrol strategies that a park manager in Chewore would require in order to achieve various management goals or answer questions related to detecting temporal and spatial trends in poaching. Required strategies are shown for standard as well as non-favourable conditions.

| **Management goal/question** | **Overall Difficulty** | **Patrol effort/strategy required to achieve goal** | |
|---|---|---|---|
| **(1) To detect temporal patterns in poaching:** | | Under standard conditions | Under less favourable conditions (low baseline poaching rate or detectability, constrained patrols, or hotspots changing over time) |
| To detect small (25%) declines in poaching with 70% power* | Very high | Not detectable, even with high patrol effort (15 7-day patrols/month). | Not detectable in all scenarios, even with high patrol effort (15 7-day patrols/month). |
| To detect medium (50%) declines in poaching with 70% power | Medium to Very high | Requires high patrol effort (12 or more 7-day patrols/month). | Achievable in most scenarios with high effort (12 or more patrols/month). However, 50% declines are not detectable when the poaching rate is low. |
| To detect large (75%) declines in poaching with 70% power | Very low to medium | Very low patrol effort required (one 7-day patrol/month). | Requires only low effort in most scenarios. However, 75% declines are only detectable with 60% power or less when the baseline poaching rate is low. |
| To detect small (25%) increases in poaching with 70% power | Very high | Not detectable, even with high patrol effort (15 patrols/month). | Not detectable in all scenarios, even with high patrol effort (15 7-day patrols/month). |
| To detect med (50%) increases in poaching with 70% power | High to Very high | Not possible. Only detectable with 60% power and high patrol effort. | Not detectable in most scenarios. Detectable with high patrol effort when the increase occurs over 3 years (as opposed to 2 years). |
| To detect large (75%) increases in poaching with 70% power | Low to High | Requires only low effort (3 or more patrols/month). | Requires low-med effort when hotspots are changing or patrols constrained, and very high effort when both. Not detectable when baseline poaching is low. |
| **(2) To detect spatial patterns in poaching:** | | Under standard conditions | Under less favourable conditions (low baseline poaching rate or detectability, constrained patrols, or hotspots changing over time) |
| Moderate (>60%) spatial overlap between real and detected poaching | Low-Medium | Requires moderate effort (6-9 patrols/month), with random or targeted patrols. | Robust to changing hotspots but requires high effort (12 patrols/month) when patrols constrained. Robust to lower poaching rate. Requires very high patrol effort (15 patrols/month) when carcass detectability lower. |
| Good (>70%) spatial overlap between real and detected poaching | Medium to Very high | Requires high effort (>9 patrols/month), with random or targeted patrols. | Robust to changing hotspots but requires very high effort (15 patrols/month) when patrols constrained. Robust to lower poaching rate. Not achievable with a lower baseline carcass detectability. |

**Notes**: Recommendations hold true regardless of spatial patrol pattern (random or targeted to areas of high previous detections), unless otherwise indicated. *A level of power of 70% was chosen for this table, because this level of confidence is likely sufficient for a park manager for whom the cost of not responding to trends may be higher (Field et al., 2004).

In a similar study, Jones et al., (2017) built spatially explicit simulations of systematic surveys of illegal activities in Gola NP in Sierra Leone. They found that unrealistic levels of survey effort would be required to detect changes in poaching over time; more than 200 1km$^2$ survey cells (30% of the study area) would need to be visited at frequent intervals to detect a 50% decline in hunting activities with reasonable power. This would be unreasonably resource intensive, so the authors recommend the collection of data through existing ranger patrols. However, my analysis here shows that ranger patrols too would not be able to detect changes in hunting activities.

The general results about the effect of patrol effort on trend detection interacted with other patrol characteristics and underlying poaching dynamics in complex ways. For example, in scenarios where patrol coverage was constrained or there were low baseline poaching levels, large (75%) changes in poaching might only be detectable at high patrol efforts. This finding highlights an important advantage of simulation models – they are able to capture the effect of important interactions between different system components, thereby yielding a more realistic understanding of the effect of individual factors like patrol effort.

Interestingly, targeted patrols did not significantly alter trend detection performance, even when underlying poaching hotspots were simulated to change over time. In a simulation model of ranger-based monitoring in a reserve in Madagascar, Keane (2010) found that spatially-biased patrols can confound temporal trends in snare detections. In a broader review, Keane et al. (2011) discuss how spatially-biased patrols can alter detection efficiency through time, confounding temporal trends. In Chewore, however, elephant poaching is not strongly clustered into hotspots, such that patrols based on previous detections are less susceptible to bias than in other contexts. A combination of changing hotspots through time and targeted patrolling in Chewore did, however, lead to a slight increase in the likelihood of detecting trends when there were none (Fig. 4.S5). Targeted patrols are more 'hit and miss' compared to spatially random patrols, in the sense that they may lead to large increases or decreases in detections over time independent of real changes in poaching, depending on the location patrolled. Lower baseline carcass detectability had only a small adverse effect on temporal trend detection, compared to the large effect observed for spatial trend detection. This may be explained by smaller sample sizes of detections in this scenario still being able to capture relative changes in poaching over time, whereas these same small sample sizes are not adequate to capture underlying spatial variation in poaching. When the absolute level of poaching was reduced from 1% versus 3%, however, reliable temporal trend detection from ranger patrols became almost impossible, even for large (75%) simulated trends in poaching. This is another sobering result; a 1% poaching rate per year translates to 30 elephants in Chewore, which may still be considered unacceptably high.

A particularly interesting result was that increases in poaching were consistently harder to detect than decreases in poaching (Fig. 4.13). Under constrained conditions, even large increases in poaching were almost undetectable even with reasonably high levels of patrol effort. This has important management implications in that an intensifying poaching threat may be hard to detect. Why was this effect observed? The discrepancy is due to important statistical anomaly which may be explained by the fact that, when investment in gathering evidence is low (as is the case with ranger patrols covering only a limited area of a large park), it is harder to find evidence of a real increase (i.e., find more carcasses) than it is to find evidence of a real decrease (i.e., find fewer carcasses over time). This is because, as detectability is not perfect, modelled patrols are generally biased towards not finding carcasses, independent of the magnitude and direction of the trend in poaching. This bias improves the power to detect decreasing trends but reduces the power to detect increasing trends. For simulated increases in poaching, it may take a while before patrols (even random ones) happen to encounter cells where poaching increases are happening. Even when they do, carcasses might have decayed by then and become less detectable. Therefore, it is difficult for patrols to perform well in this scenario. However, with declining trends, it is not a case of trying to find new poached carcasses and failing. Even if declines are not happening in patrolled areas, carcasses are decaying quickly and becoming less detectable, so declines in detections happen both in areas where decline are actually happening, and in other areas. Supporting this idea, examination of trends in detected carcasses in a number of simulation replicates across different scenarios show that ranger carcass detections take a while to increase after the simulated increase in poaching starts, whereas ranger detections decline more immediately after a declining trend in poaching. This reasoning is also supported by the fact that increases in poaching simulated to occur over 3 years (rather than the 2 years used for all other simulations) were more detectable, because patrols were allowed more time to detect the change (Fig. 4.S5). These results are similar to that of (McConville et al., 2009) , who found that the magnitude of declines in saiga antelope populations can be overestimated by aerial surveys because true population sizes are underestimated at lower population densities.

Of all patrol characteristics and strategies, patrol effort had the largest overall effect on spatial detection performance. At low patrol efforts, small increases in effort led to large increases in performance (e.g., increasing effort from 3 to 9 patrols/month led to a 50% increase in spatial congruence between real and detected poaching). Notably, however, increasing patrol effort beyond 9 patrols per month (a medium level in the context of Chewore) led to only very small increases in how well reported poaching captured true spatial patterns in poaching. This held true when there were additional constraints on detections (e.g., lower detection probabilities and constrained patrols). Thus, park managers with limited patrol budgets need not invest in very high patrol effort to adequately capture spatial patterns in underlying poaching. This is a significant result when one considers how important understanding spatial patterns in poaching is to the patrol strategies developed by park managers (Critchlow et al., 2015). Indeed, identifying spatial poaching hotspots is the most common use of ranger-collected data in Chewore (see Chapter 6, Table 6.1). This result that spatial pattern detection requires a threshold sample size of detections in order to adequately capture the range of spatial variation in underlying poaching patterns. This is also borne out in the observed effect of reduced carcass detectability having a significant adverse effect on spatial detection performance. Similar to the effect of patrol effort, this is likely due to small sample sizes that are inadequately representative.

Constraining patrols to areas closer to ranger stations had a notable (and perhaps obvious) adverse effect on spatial trend detection, as carcasses in less frequently patrolled areas were not accounted for. This may be an important driver of spatial bias in actual ranger-collected data in Chewore. Indeed, the empirical data set of 187 poaching incidents in Chewore revealed large spatial gaps in detections and Chapter 3 confirmed that these were in areas that are difficult to patrol and therefore less often visited (Kuiper et al., 2020). Surprisingly, patrols simulated to target areas of higher previous carcass detections performed very similarly to spatially random patrols. One of the most common criticisms of ranger-based monitoring data is that it is typically gathered from spatially biased patrols and so needs to be interpreted with caution (Critchlow et al., 2015). In a comprehensive review of ‘messy data’ for conservation, Dobson et al. (2020) highlight spatial bias as a common problem with ranger-collected data and other similar datasets like citizen science observations. Indeed, accounting for this spatial bias was a primary motivation for the methods developed in Chapter 3 of this Thesis (Kuiper et al., 2020). The virtual ranger model presented here, however, shows that basing patrols on previous detections does not lead to significant patrol bias if the underlying distribution of poaching is sufficiently spread out, as is the case in Chewore. This is discussed further below.

*Spatially targeted patrols do not bias results*

Scenarios in which patrols actively targeted areas where there were high detections of poached carcasses in the past performed very similarly to patrols that were completely spatially random. One might expect that the targeted strategy would result in 'confirmation trap' effects whereby detections are biased away from true patterns and towards a set of high patrol/detection areas (Dobson et al., 2020). This would have obvious effects on how closely the spatial pattern of detections match true spatial patterns (see Chapter 3; Kuiper et al., 2020), but would also confound temporal trend detection in cases where targeted areas do not adequately represent park-wide trends. Yet no evidence was found for these effects in my model, even though the probability of patrolling a cell was directly proportional to previous detections (a cell in which three carcasses had been detected in previous time steps was three times more likely to be patrolled than a cell in which one carcass had been detected). Even when hotspots were simulated to change through time (which would be expected to cause targeted patrols to perform particularly badly as previous detections would not be a good predictor of future poaching locations), no such effect was observed.

Scenario exploration helped determine that this was due primarily to the relatively low levels of aggregation in the underlying poaching data, whereby simulated poached carcasses were fairly well spread out across Chewore based on parameterisation using the spatial models of empirical data from Chewore (Chapter 3; Kuiper et al., 2020). When the aggregation of carcasses was simulated to levels much higher than observed for Chewore (Fig. 4.17), then targeted patrols performed more poorly. Thus, unless carcasses are highly aggregated in space, targeted patrols are unlikely to focus exclusively on a few 'hotspots' of high previous detections because previous detections are likely to be more spread out in the first place. These results challenge the commonly cited critique of ranger patrol data and indeed many other forms of sampling – that is, spatial bias towards areas of expected high detections. The suitability of spatially targeted sampling will be context-specific and must be weighed up against the obvious advantages of potentially higher detections or poacher apprehensions from well-informed biased sampling (Critchlow et al., 2016). The intuitive negative effects of spatially targeted patrols did become apparent in the simulation with highly clustered carcasses (i.e., when there were distinct poaching hotspots), which may be the reality in many contexts (see Rashidi et al., 2017). Also, as discussed above, targeted patrols may be more susceptible to detecting trends when there are none, even when carcasses are not heavily clustered.

Importantly, this result demonstrates a key advantage of the virtual ranger simulation approach: it can produce non-intuitive results that challenge the simplistic assumptions we make about expected effects, suggesting that decisions based on intuition alone can be misleading in some contexts. Furthermore, the mechanisms behind unexpected effects can be better understood through virtual experimentation (as I have done through altering the simulated level of the spatial clustering/spread of carcasses). Finally, this result also provides evidence that the virtual ranger model is functioning as expected and accurately representing interacting processes. Targeted patrolling would be expected to produce more biased results when hotspots are more concentrated as patrols are more likely to 'latch on' to particular areas of high poaching intensity and keep patrolling there.

*Critical reflection on the virtual ecologist approach*

The virtual ranger model developed here may be considered a general framework with potential application to a wide variety of contexts. The essential elements are (a) an 'operating model' that represents the study system, and specifically the underlying spatial pattern and temporal trend of the particular system process of interest, and (b) a ranger observation model that represents the process by which data on this process are collected. While these essentials are common to virtual ecology models already developed for many different types of wildlife monitoring (Jones et al., 2017; Ling and Milner-Gulland, 2007; Nuno et al., 2015), the framework I develop in this Chapter is tailored to an observation process involving ranger patrols, with the unique features that such a monitoring process entails. Various features of the ranger patrol process are modifiable within the model (such as effort, coverage, detectability, and the size and path of individual patrols), allowing for adaption to ranger-based monitoring in other contexts. Similarly, the abundance and spatio-temporal pattern of the underlying system process (in my case elephant poaching) can be modified to represent any number of biodiversity or threat patterns for which rangers might collect data.

It is important to note that the focus of the virtual ecologist approach is less on precisely representing the true state of the system, but rather on creating a realistic set of possible scenarios and then testing whether data collected according to a defined observation process are a robust representation of these scenarios. The approach allows for the experimental variation of key features of this process (e.g., sampling intensity, detectability biases) and interpretation of how each of this affects how closely monitoring data represent the simulated reality. Indeed, a significant advantage of this method is that it avoids the costs of real-world experimentation (Milner-Gulland and Shea, 2017). Nonetheless, the usefulness of the results for reality is still dependent on understanding the processes and approximate parameter ranges and functional forms that operate in the real world. This is why I chose to closely parameterise the models developed here to the current elephant poaching and ranger patrol dynamics in Chewore. It follows that the fruitfulness of applying the model developed here to other contexts will in large part depend on the quality of data available to parameterise the operating and observation models.

One significant process that I did not include in this virtual ranger model is the effect of deterrence, whereby the spatial pattern of ranger patrols influences where poachers choose to poach (Moore et al., 2018). Such a process may have large implications for patrol-based trend detection. The extent to which such a process occurs in Chewore is not clear, however. Also, the underlying empirical data used to parameterise the simulated distribution of poached carcasses represents the ultimate outcome of several processes affecting the spatial pattern of poaching. Thus, the effect of any real-world deterrence will be represented in these data, and the simulations based on them. Another caveat is the method used for measuring the performance of spatial trend detection, that is, the correlation between real and detected poaching. The challenge with the correlation-based approach I employed is in its interpretation. How large must the difference in the spatial correlation performance between two patrol strategies be in order to be significant enough for managers? Visual plots of the spatial distribution of real versus detected poaching are more helpful in this respect but are difficult to turn into measurable quantities.

Similarly, the method used for assessing temporal trend detection performance may be unduly conservative (i.e., underestimate patrol performance) when measuring the power to detect small to medium temporal changes in poaching. This is because trends in the underlying simulated data itself may not be statistically significant. This, in turn, may be due to a combination of small sample sizes, random variation in poaching from month to month, and the small magnitude of simulated change (see, for example, how the simulated data in the top panel of Fig. 4.19 in do not show a statistically significant trend for some replicates even though a decline in poaching was simulated). Finally, the methods used to assess spatial and temporal trend detection performance take into account all carcasses detected, regardless of how old the carcass is. In reality, managers might use only data on fresh carcasses to detect trends, for example. The majority of detections did however constitute carcasses less than a year old (due to reduced detectability for older carcasses). Assessing the sensitivity of trend detection to whether or not all or only fresh carcasses are used is an area for future exploration. More generally, the quantitative criteria used to assess the power of patrols to detect trends may be considered too strict, and more qualitative indications of trends from ranger-collected data (which may not be *statistically* significant) are appropriate and sufficient for management.

*Conclusions*

Under current conditions in Chewore (intermediate patrol effort that is often spatially constrained), ranger-collected data are unlikely to have strong quantitative power to detect trends in poaching. This finding does depend on aspects of patrol performance that can be manipulated by managers, however. Different patrol characteristics (effort, coverage, spatial pattern, etc.) have markedly different effects on the accuracy and precision of patrol data in terms of capturing underlying poaching patterns, with some non-intuitive outcomes (such as spatially random and spatially targeted patrols performing very similarly or increases in poaching being far less detectable than decreases of the same magnitude). Furthermore, the relative importance of different patrol characteristics for achieving reliable detection performance depends to a large degree on the particular management question (the magnitude of change in poaching that managers wish to detect reliably, for example). These results emphasize the importance of being clear about what the goals of monitoring are and assessing monitoring designs in light of these goals. In the context of Chewore, results caution against placing too much confidence in the power of ranger-based monitoring to answer certain management questions and encourage more careful consideration of appropriate ends for ranger-collected data.

## 4.5. Supplementary Material

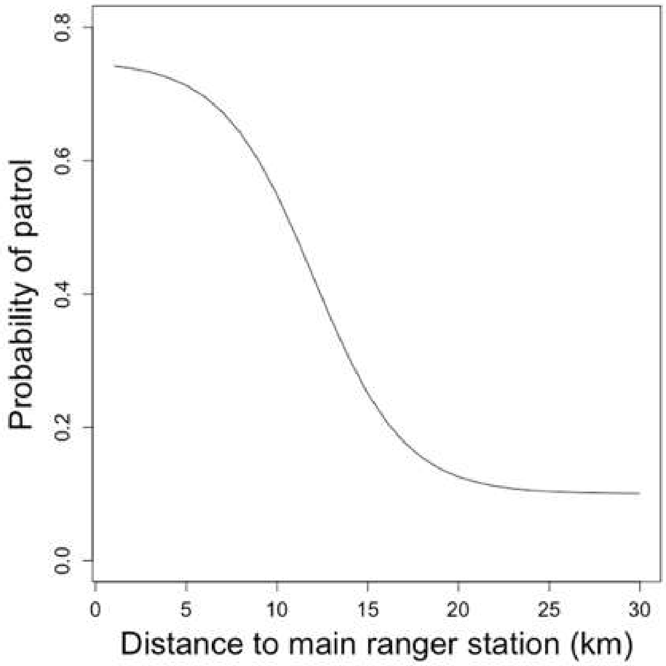



**Figure 4.S1.** The half-normal function used to simulate the change in the probability of a park grid cell being patrolled as a function of its distance from the nearest main ranger station (see Fig. 4.3 in the main text).

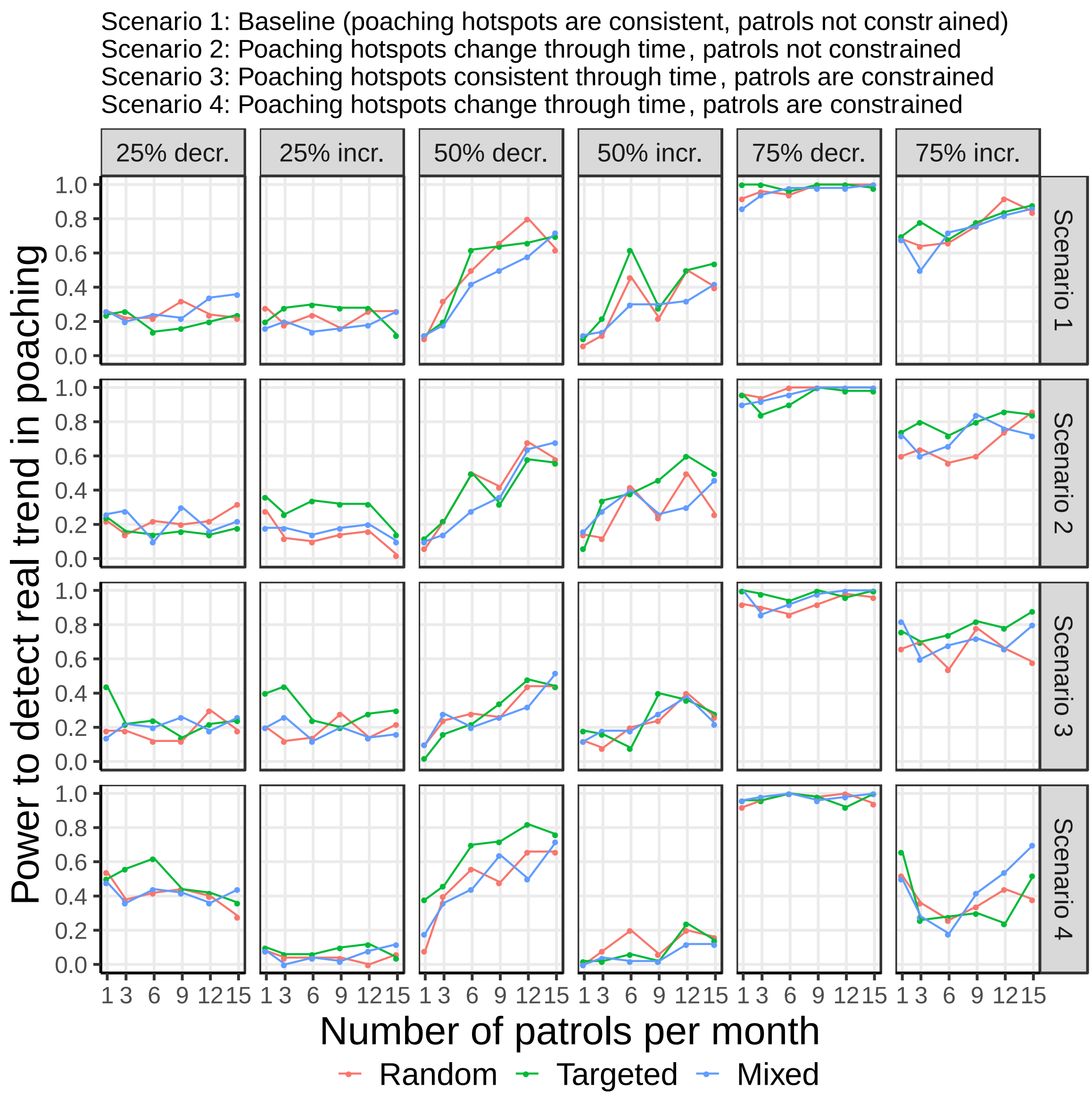



**Figure 4.S2**. The effect of various ranger patrol characteristics on the performance of ranger-collected data at capturing temporal trends in elephant poaching of different magnitudes. Trends were simulated to occur over 24 time steps (representing a 2-year period), from a baseline poaching rate of 90 elephants p.a. (3% of the population). Power is measured as the proportion of simulation replicates for which a statistically significant change in ranger-detected carcasses was observed in the year before versus the year after the trend in poaching. Patrol characteristics include effort (number of patrols per month), spatial patrol pattern (random or targeted to areas of high previous detections), and patrol coverage (constrained to areas near the main ranger stations or not). The effect of poaching hotspots changing over time is also shown.

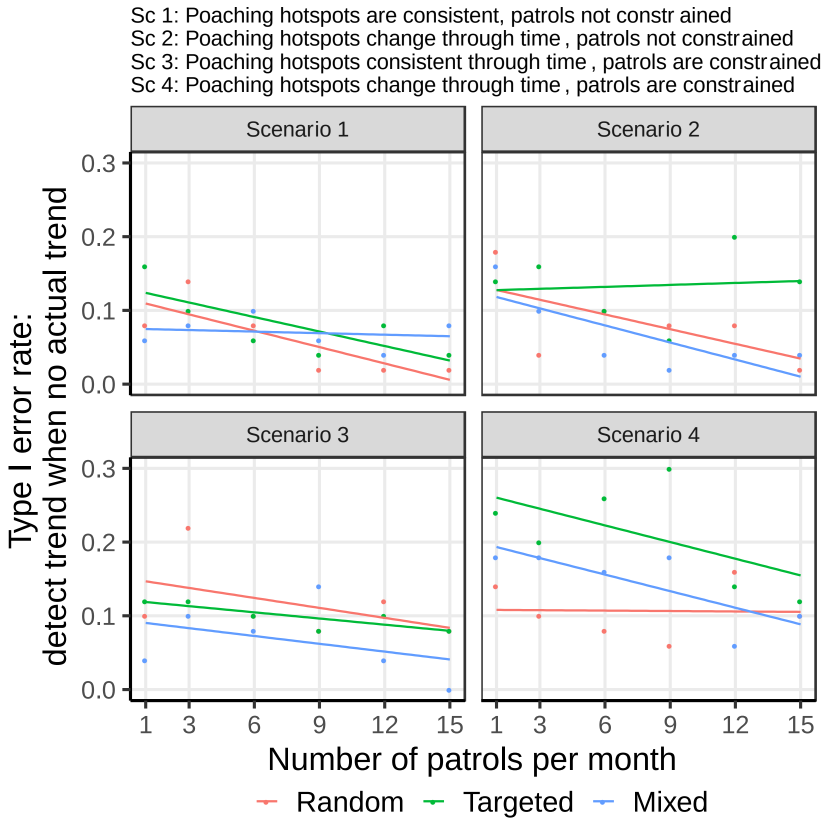



**Figure 4.S3.** The effect of patrol characteristics on the probability of ranger patrols making the error of recording a significant change in poaching levels when in fact there was no temporal change in poaching. Measured as the proportion of simulation replicates for which a statistically significant trend in carcass detections was observed. A poaching rate of 90 elephants per year (3%) was simulated and remained constant. Lines represent simple linear model fits.

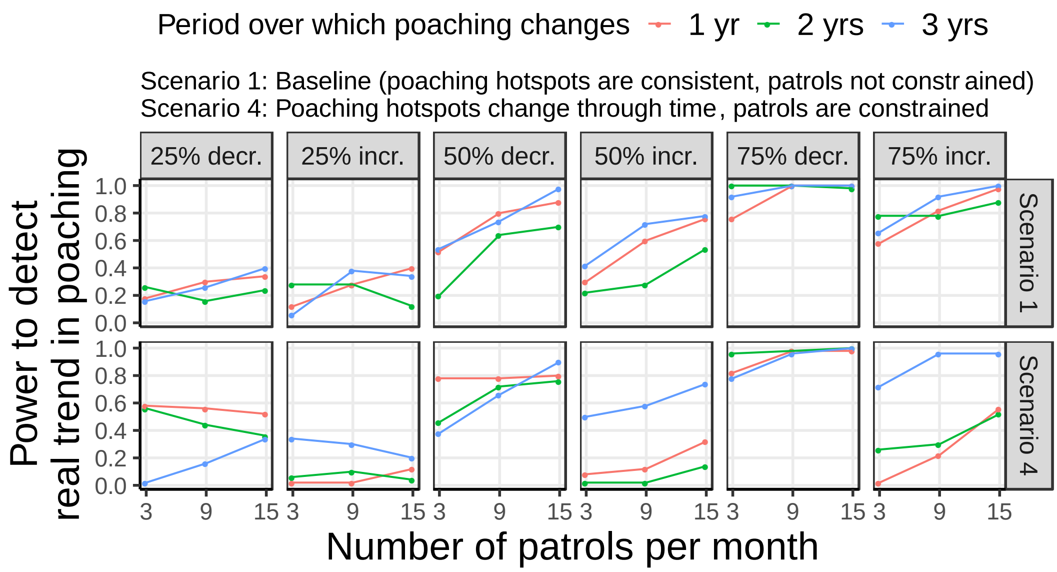



**Figure 4.S4.** The effect of the period over which the simulated poaching change occurs, on the power of patrols to detect temporal changes in poaching (25%, 50%, and 75% increases and decreases from the baseline). Scenarios with and without poaching hotspots changing through time, and constraints on patrols, are shown. Data are shown only for targeted patrols (results for random patrols were very similar).

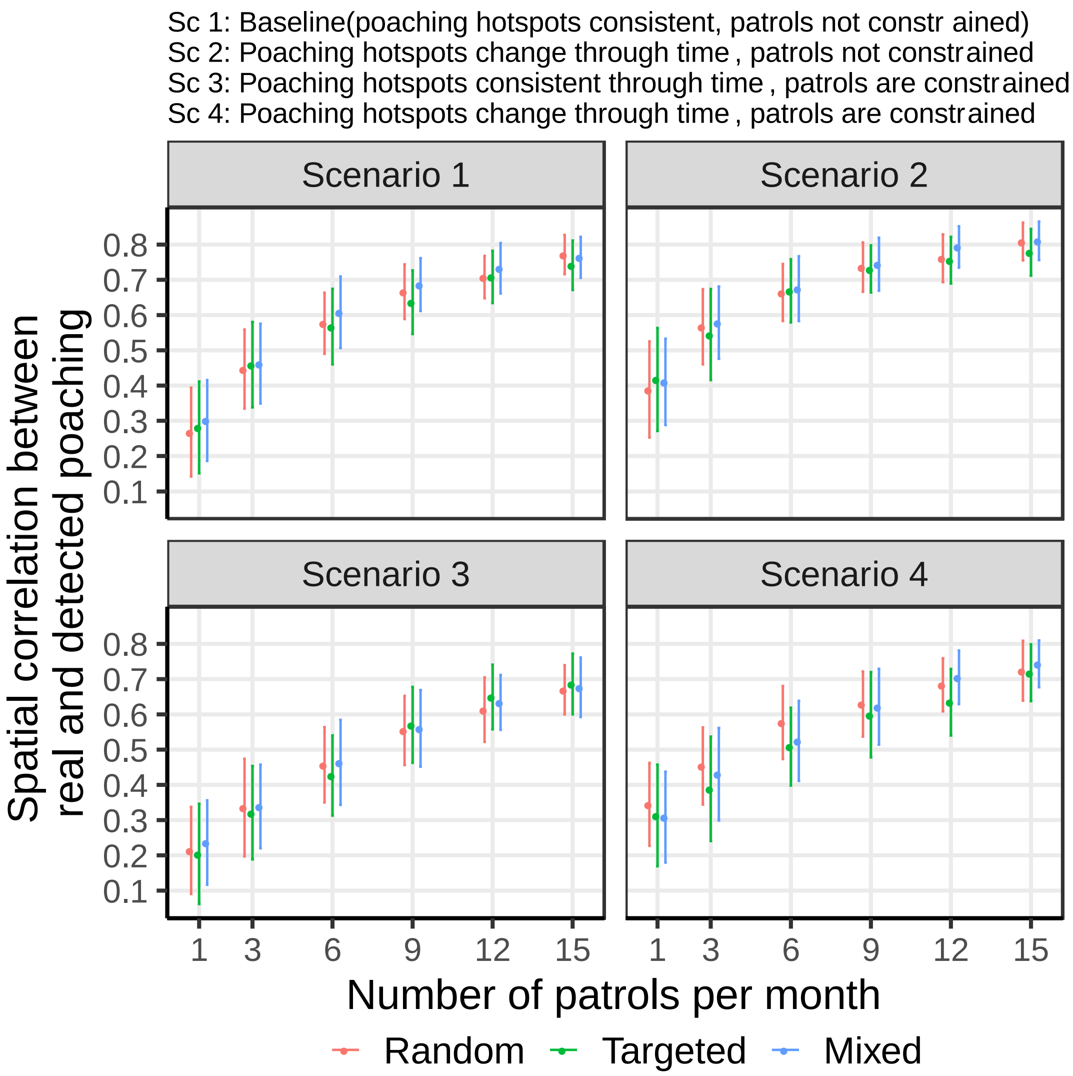



**Figure 4.S5.** The spatial congruence between real and detected poaching: the effect of various patrol characteristics on the cell-wise spatial correlation between the real number of elephants poached and the number of poached elephant carcasses detected in each of Chewore's 712 grid cells. Simulated poaching intensity was constant at 3% (90 elephants per year) and correlation was determined for a 3-year period in the middle of the simulation period.

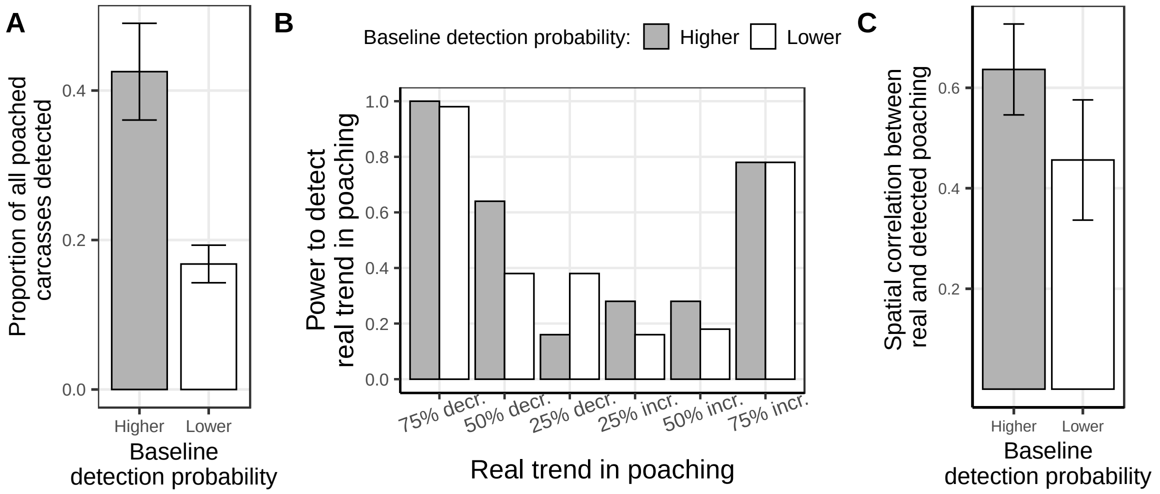



**Figure 4.S6.** The effect of the baseline detectability of poached elephant carcasses (Higher - 70% and Lower - 50%, see methods text) on (A) overall carcass detections, and on the performance of ranger patrols at capturing (B) temporal and (C) spatial patterns in poaching. Data are shown for an intermediate level of patrol effort of 9 patrols per month (the closest to the current reality in Chewore), and only for targeted patrols (results for spatially random and mixed patrols were similar).

# Chapter 5: Ranger perceptions of, and engagement with, monitoring of elephant poaching

## 5.1. Introduction

Monitoring changes in biodiversity and threats within protected areas is essential for understanding their status and evaluating conservation interventions. Collecting systematic, robust data on features like wildlife distribution or poaching levels requires technical capacity and resources, as do later analytical stages in the adaptive management cycle (Canessa et al., 2015). Therefore, when resources for management are scarce, more direct interventions (like anti-poaching operations) may be prioritised over baseline monitoring (Nuno et al., 2017). Rangers across the world spend large amounts of time patrolling extensive areas and are therefore well-placed to make observations of illegal activities and biodiversity. Ranger-based monitoring is thus a valuable management resource, providing a cost efficient alternative to skill and resource intensive ecological surveys (Gray and Kalpers, 2005; Kuiper et al., 2020). Rangers must, however, balance collecting data with other patrol-based activities such as direct law enforcement and anti-poaching (Moreto and Matusiak, 2017; Stokes, 2010). Ranger-collected data may also be subject to systematic bias because patrols are seldom consistent over space and time, and favour certain areas and species over others (Dobson et al., 2019).

I use the term 'ranger' to refer to "a field-based operative whose regular work involves surveillance, protection and maintenance of species and ecosystems" (Belecky et al., 2019). I define ranger-based monitoring as the collection of data by rangers, which may include evidence of illegal activity, animal sightings and behaviour, and vegetation status (Gavin et al., 2010). The global programme for the Monitoring of the Illegal Killing of Elephants (MIKE) is a prominent example of the value of ranger-based monitoring. Rangers across 90 MIKE sites in 30 African and 13 Asian countries report elephant mortality data from regular patrols. The resultant data is used both for local protected area management and to inform international wildlife trade policy (CITES Secretariat, 2019). The large information potential of ranger-collected data has encouraged quantitative research into understanding and overcoming biases inherent in these data, such as effort-adjusted indices (Dobson et al., 2019) and hierarchical statistical models (Critchlow et al., 2015). Furthermore, quantitative models have been developed for translating biased data into future patrol strategies (Fang et al., 2017). Significantly less work, however, has investigated the social and human dimensions of ranger-based monitoring, such as ranger occupational culture, and how these intersect with the day-to-day realities of being a ranger. Therefore, an important prerequisite for understanding the mechanisms underlying the process of ranger-collected data is missing; modelling alone cannot provide the insights required for more effective protected area management.

A recent survey of over 7100 government rangers across 28 Asian and African countries revealed that 50% of rangers lack access to clean water, one in three contracted malaria in the preceding year, and less than a fifth of the 74% who are married were able to live with their spouses (Belecky et al., 2019). Rangers' salaries are often low, and they feel under-equipped, while 81% of rangers believed their jobs were dangerous. Seminal qualitative work on ranger perceptions has provided rangers' insights into poacher motivations (Moreto and Lemieux, 2015), the occupational stresses they face (Moreto, 2016a), their relations with local communities (Moreto et al., 2017), and their understanding of professionalism and misconduct (Moreto, Brunson & Braga, 2015; Massé, 2020). These studies are unified in their demonstration of the value of meaningfully engaging rangers in conceptualising and tackling conservation problems, rather than seeing them as passive nodes through which conservation strategies are enacted. The well-being and perceptions of rangers are important both ethically (they are at the frontline of conservation management), and practically (the sustainability and rigour of ranger-based monitoring relies on commitment from rangers).

Drawing on these insights, I argue that understanding the value that rangers ascribe to data collection requires understanding the context of their broader occupation, and specifically ranger occupational culture. Occupational culture encompasses the shared norms, values, beliefs, and priorities of members of a particular occupation (Van Maanen and Barley, 1982). The culture developed among a group of people in the same occupation defines what is valued, emphasised and accepted in this community, and therefore influences behaviour and conduct (Christensen & Crank, 2001; Schein, 1990). Occupational culture focuses on human behaviour and social processes through the lens of occupational communities, rather than the lens of the organisation, to help explain social behaviour and performance in the workplace (Van Maanen & Barley 1982). Glomseth, Gottschalk, & Solli-Sæther (2007), for example, identified four dimensions of occupational culture amongst police officers in Norway, finding that the extent and nature of 'team culture' had a significant influence on knowledge sharing amongst officers during police investigations. Importantly, occupational culture has a direct bearing on performance at work. Occupational culture is thus a useful lens to understand how members of an occupation (rangers) engage with a particular aspect of their work (data collection and monitoring), in order to identify pathways to more effective organisational practice.

Using a case study of rangers involved in a long-term programme for monitoring and managing elephant poaching in the Zambezi Valley, Zimbabwe, I draw on insights from occupational culture as well as existing work on ranger perceptions and culture to examine and understand a core aspect of rangers' work, namely data collection and monitoring. I ask the following questions:

1. How do rangers perceive their occupation: what values and motivations typify their work?
2. What importance do rangers ascribe to data collection within this broader occupation?
3. Are rangers involved/aware of how the data they collect are used for conservation management?
4. What influences how engaged rangers are with ranger-based monitoring?

Finally, I discuss how rangers' level of engagement with monitoring might affect data quality and the evidence-based management that depends on it.

## 5.2. Methods

*Study area and field work*

I conducted research in two adjacent protected areas in the Zambezi Valley, Zimbabwe: Chewore Safari Area, and Mana Pools National Park, both managed by the state wildlife authority. Together with Sapi Safari Area, these form the Mana-Chewore World Heritage Site (see Fig. 5.2 in Chapter 2 for a map of the study area). The elephant population in the broader Zambezi Valley has declined from *c.* 20 000 in 2003 to *c.* 11 000 in 2014, mainly due to poaching (ZPWMA, 2015). Chewore, Mana and Sapi are MIKE (Monitoring of the Illegal Killing of Elephants) sites, with large numbers of poached elephant carcasses detected by rangers in recent years (CITES Secretariat, 2019). Rangers encounter elephant mortalities (poached and natural) while on regular patrols, with data from these sites reported annually to MIKE offices at regional and global levels. I visited two ranger bases in each of Chewore and Mana, between the 1st and 24$^{th}$ of August 2018, living in ranger accommodation in close proximity to rangers themselves. This allowed for many informal conversations with rangers, supervisors, and observation of their daily activities (recorded using field notes). I also accompanied rangers on two day-long patrols to observe first-hand how rangers collect data.

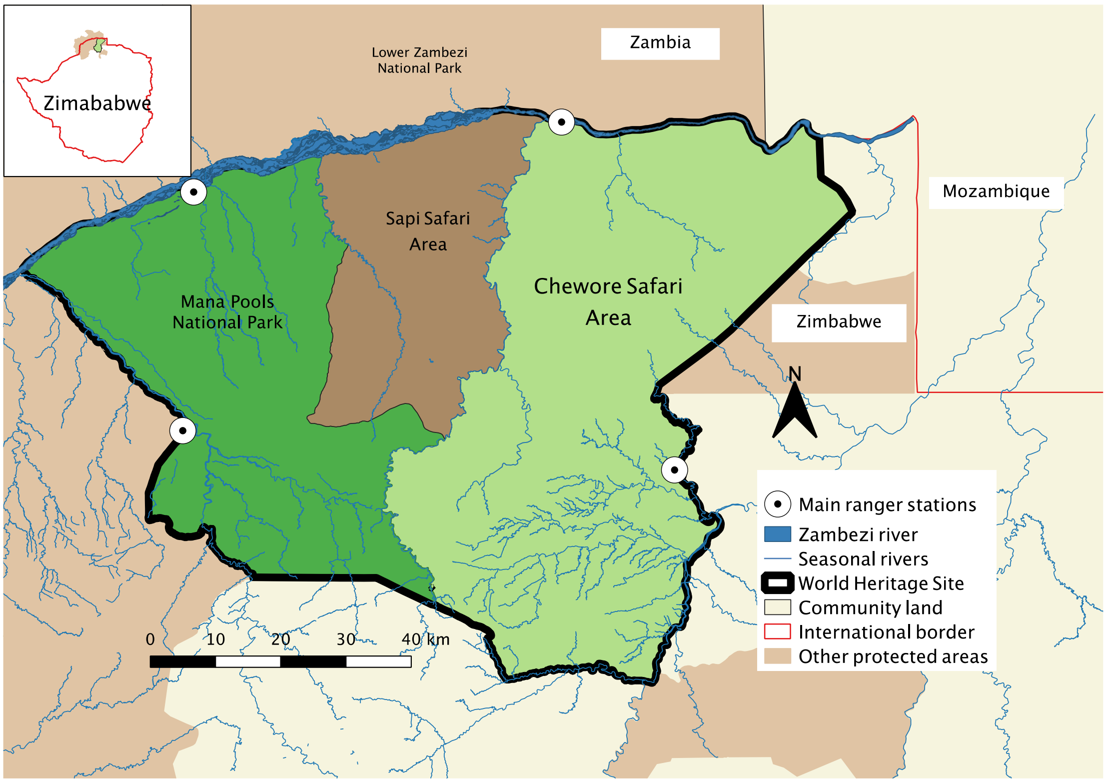



**Figure 5.1.** The Mana-Chewore World Heritage Site, showing the four ranger bases at which interviews were conducted.

*Interviews, respondent recruitment and thematic analysis*

I conducted individual semi-structured interviews with park rangers and their supervisors (Table 5.1). The semi-structured format helped balance the need to stimulate discussion rather than elicit particular answers, while also maintaining focus on my research questions (Newing, 2010; Young et al., 2018). Two types of respondent were interviewed: rangers (n=23) and their immediate on-site supervisors (n=8), out of a total of c. 94 rangers and 11 supervisors across the two protected areas. Each respondent was interviewed individually in a private room. At each of the four ranger stations, rangers were randomly selected for interview from those available in camp and not out on patrol (rangers take a few days off between extended patrols). I continued sampling until saturation was achieved, i.e. the point where more interviews yielded minimal new information (Ritchie, Lewis & Elam, 2013; Table 5.1). Rangers are directly involved in the collection and reporting of monitoring data, while supervisors are responsible for planning patrol deployments and supervising data collection. Both groups are employed by the Zimbabwe Parks and Wildlife Management Authority (ZPWMA). Each ranger interview comprised several broad areas of discussion (working conditions, the nature of patrols, perceptions of the value of data collection, and involvement in data management and analysis), with several questions in each section (an interview guide is included in Appendix 2 of this Thesis). Supervisor interviews focussed on the extent to which elephant carcass data were used for management (analysed in Chapter 6), but also included questions on ranger supervision and monitoring (analysed here).

Based on triangulation among interviews, personal observations, and the general impression given by respondents, I judged that responses were honest and did not find evidence for any strong social desirability bias. I established rapport with respondents by approaching them as a young student with no ulterior agenda, emphasising that he was not affiliated with any NGOs operating in the area or with the MIKE programme, such that respondents were willing to candidly share their frustrations. All respondents were male Zimbabwean nationals, except for two female rangers (there are very few female rangers overall). The families of the majority of respondents lived in towns outside the Zambezi Valley region.

**Table 5.1.** The number of rangers and their supervisors interviewed at each of four ranger stations in the Zambezi Valley, Zimbabwe.

| **Site and ranger station** | **Rangers interviewed (mean # of years working at site)** | **Supervisors interviewed (mean # of years working at site)** |
|---|---|---|
| *Chewore safari area* | | |
| Mkanga ranger station | 9 (4.2 $\pm$ 2.2 years) | 2 (1.5 $\pm$ 0.7 years) |
| Kapirinhengu station | 5 (10.3 $\pm$ 5.0 years) | 2 (4.6 $\pm$ 6.0 years) |
| *Mana pools national park* | | |
| Mana pools station | 7 (9.4 $\pm$ 4.0 years) | 3 (5.63 $\pm$ 5.1 years) |
| Zavaru station | 2 (9 $\pm$ 3.2 years) | 1 (9 years) |

I analysed interview responses using thematic analysis to identify patterns of meaning in the data and then developed a narrative account of key themes in relation to the research questions (Braun and Clarke, 2006). Analysis started with a period of immersion in the data followed by the generation of flexible notes and annotations (Newing, 2010). *Nvivo* software (QSR International Pty Ltd, 2018) was then used for thematic analysis, using a combination of deductive (focussed on my prior research questions) and inductive (bottom-up) coding (Braun and Clarke, 2006). The importance of a theme was judged either by its prevalence (repeat occurrence across and within respondents) or by how informatively it spoke to the research questions (Braun and Clarke, 2006). This process was repeated once to check for reliability. I also categorized ranger respondents based on whether or not greater knowledge of how the data they collected are used would motivate more engaged future data collection. This involved coding the responses of each respondent (across a number of questions) that spoke directly to this theme, and then making a categorization assessment that reflected their overall sentiment. A conservative approach was taken to increase reliability, by including 'mixed sentiment' and 'uncategorised' categories for cases where the sentiment of the respondent was not clear. Responses were kept confidential and anonymous, and each respondent gave prior and informed consent for their participation. All procedures were granted ethical approval by the Human Research Ethics Committee at Oxford University (CUREC REF: R58336/RE001**)**.

## 5.3. Results

*Overview of ranger-based monitoring in the Zambezi Valley*

Rangers described having diverse duties, including patrols, law enforcement, fire management, road maintenance, monitoring of trophy hunts, and office duties (amongst others). Their primary responsibility was routine multi-day patrols. Typically, four rangers are deployed by a vehicle to a particular area of the park, either at a temporary or permanent camp, and remain for seven days. Each day is spent patrolling the surroundings in different directions (4-8 hours per day, within 5-10km of the base). A secondary patrol strategy involves rangers changing base every night or two, covering a more linear area. Less common patrol types include day-long foot patrols from the main station, and 1-3-day vehicle patrols. Patrol areas are chosen based on expected illegal activity, animal distribution, water availability, and accessibility (Table 5.2). Monitoring illegal activities (elephant poaching, fish poaching, subsistence bushmeat hunting, gold panning, livestock encroachment, and others) is the main purpose of patrols. Rangers record evidence of illegal activity, large animal sightings, and water and vegetation status using notebooks (Table 5.2). Handheld devices for recording observations and patrol routes have recently been introduced but are not yet widely used. After patrol, rangers share results with their supervisors in a debrief session and discuss future patrol strategies. The patrol leader then compiles a handwritten report, describing the routes used each day and all notable observations (Fig. 5.3).

A review of patrol reports showed that the directions of daily patrol routes and notable observations were consistently reported, with variation among stations in the detail provided

(Fig.3). GPS records of observations and patrol locations were inconsistent, however. Some patrols are not recorded, evident from comparing entries in patrol books to ranger interview accounts of recent patrols. Some patrols included future patrol recommendations. Detailed recording of elephant mortality is conducted at all stations as part of the MIKE programme (Fig. 5.4), leading to significantly more detail and consistency (e.g., GPS locations, times and dates, auxiliary information) in reporting of elephant mortalities compared to other illegal activities and animal sightings.

**Table 5.2.** A typology of data types collected by rangers in the Zambezi Valley, Zimbabwe. Data types are listed in order priority as judged by their frequency in rangers' responses.

| **Type of data collected** | **Purpose** |
|---|---|
| Evidence of illegal activity (carcasses, poacher camps, poacher spoor, snares) | Guide future patrol deployments. Measure anti-poaching effort and performance |
| Key animal species sightings (elephant, buffalo, lion, leopard, various antelope) | An area of higher animal abundance requires more frequent patrolling |
| Water status (whether rivers and springs are dry or active) | Water points attract animals and are targeted by poachers. Rangers may also depend on water access during patrols |
| Vegetation status | Seasonal vegetation change is large and affects animal distribution and hence patrol strategies |
| Animal behaviour | Distress can indicate poacher presence. |
| Animal trophy quality | Discern potential hunting trophies |
| Animal health | Poor health can indicate water scarcity, disease or the need for supplementary feeding |

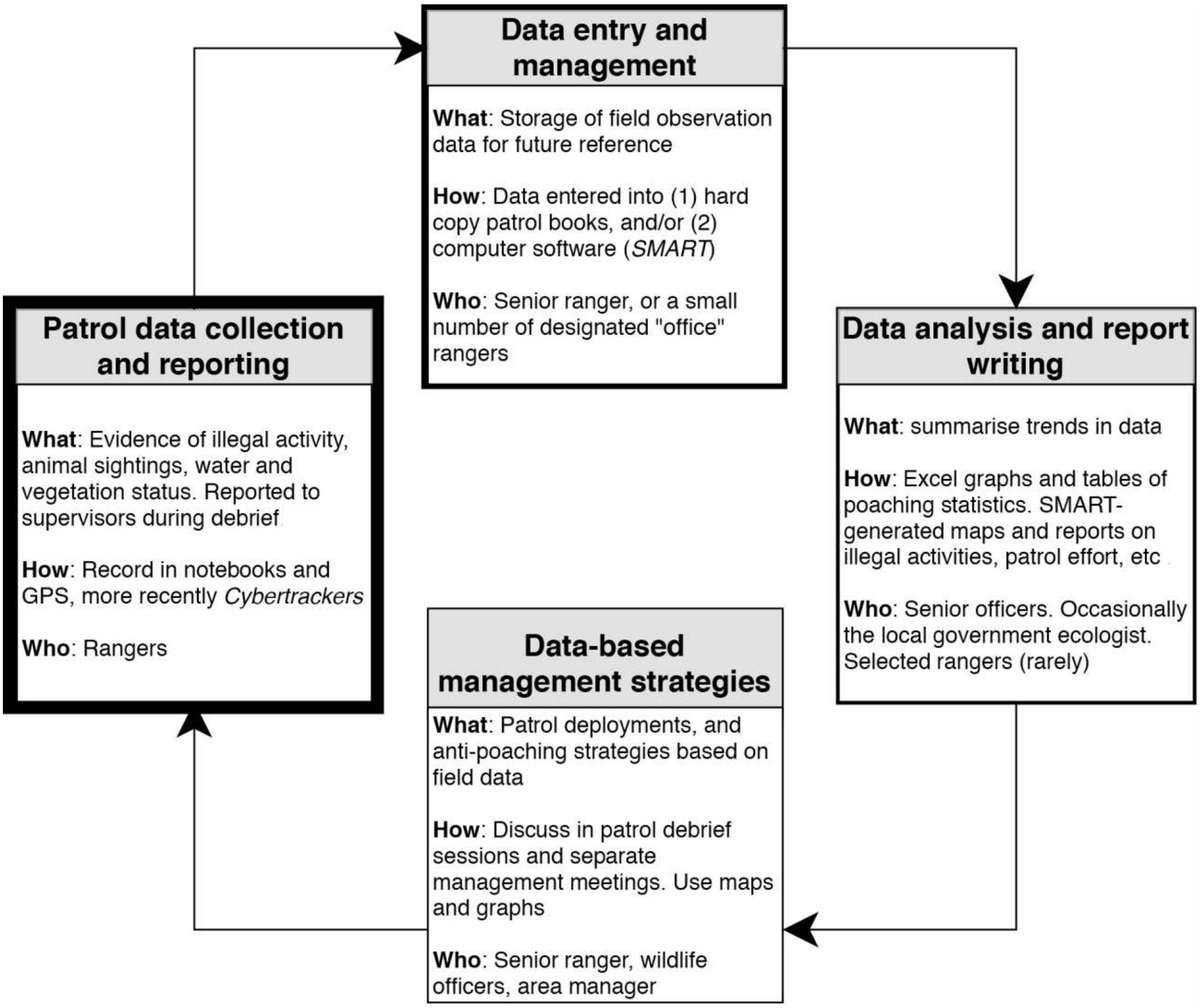



**Figure 5.2.** The data cycle for the ranger-based monitoring and management system, showing four distinct stages. Line thickness around each stage represents the level of engagement of rangers in that stage (based on interviews and personal observations from Mana-Chewore).

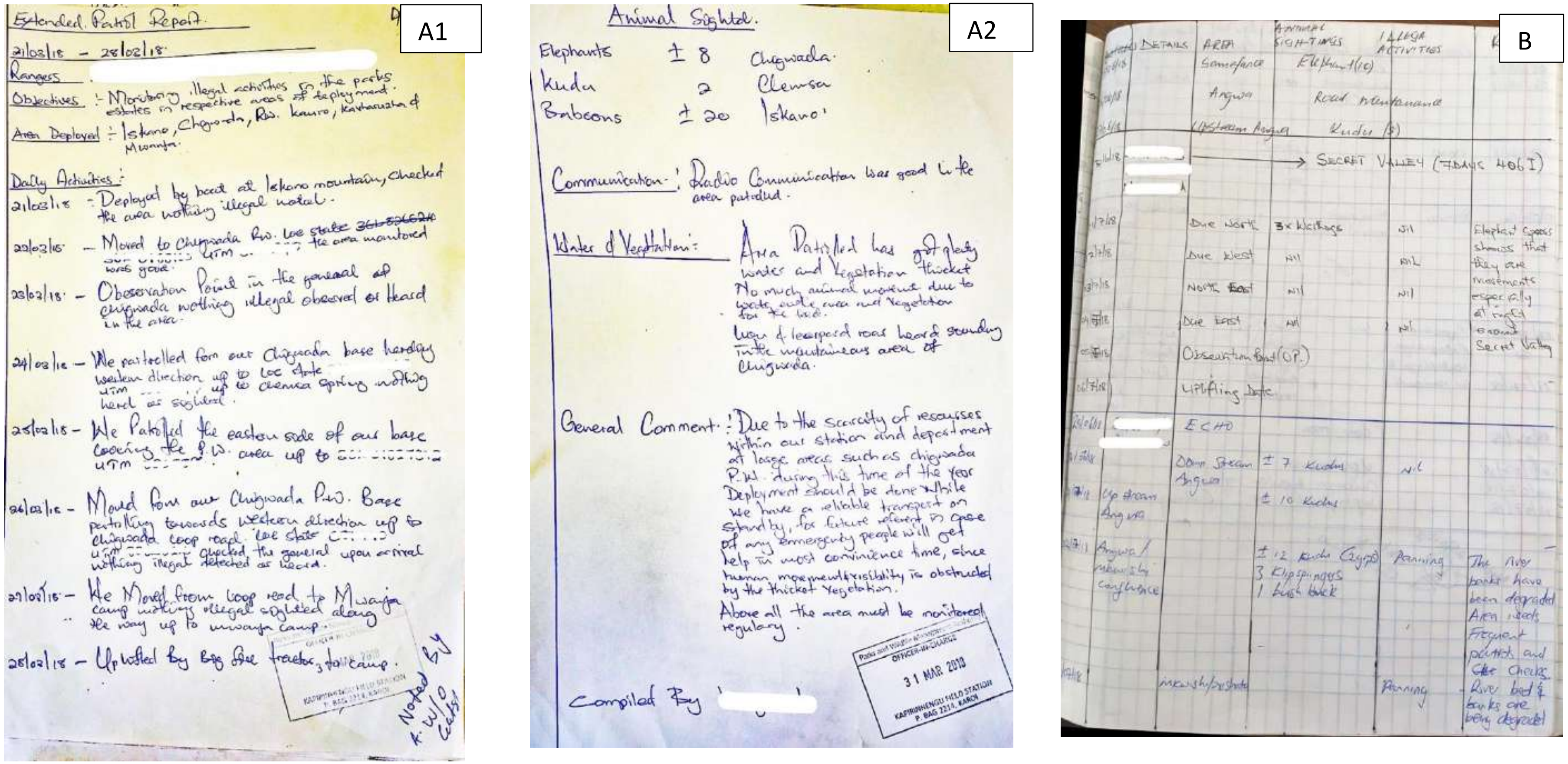
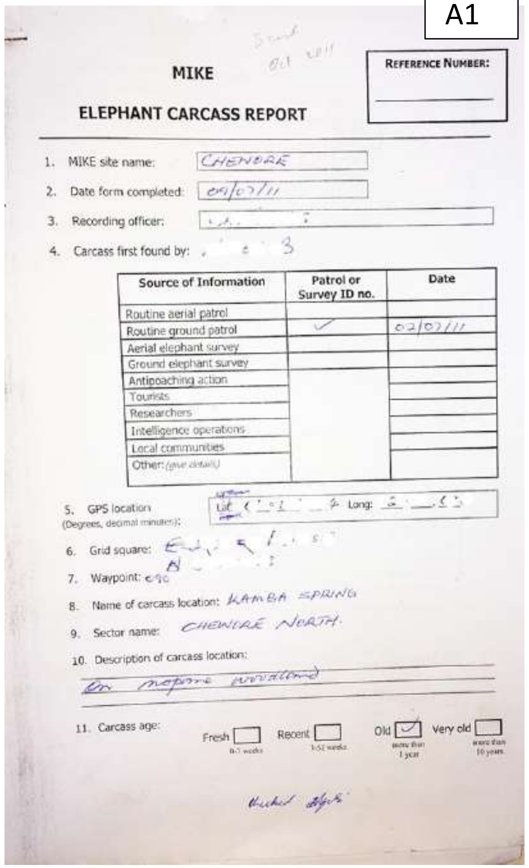



**Figure 5.3.** Example of extended patrol reports from two different ranger stations in Chewore (2018). A1 and A2 constitute one patrol report (8-day patrol), while B shows data from three separate 7-day patrols (only the middle report is shown in full). Ranger names and GPS locations have been removed.

A1


MIKE

ELEPHANT CARCASS REPORT

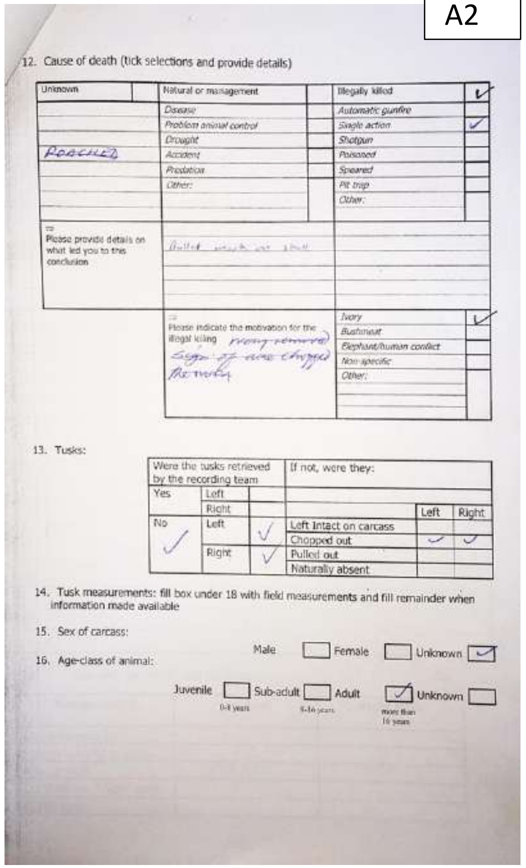
REFERENCE NUMBER:

1. MIKE site name: CHEWORE
2. Date form completed: 05/07/11
3. Recording officer:
4. Carcass first found by:

| Source of Information | Patrol or Survey ID no. | Date |
|---|---|---|
| Routine aerial patrol | | |
| Routine ground patrol | ✓ | 02/07/11 |
| Aerial elephant survey | | |
| Ground elephant survey | | |
| Antipoaching action | | |
| Tourists | | |
| Researchers | | |
| Intelligence operations | | |
| Local communities | | |
| Other: (give details) | | |

5. GPS location (Degrees, decimal minutes): Lat: Long:
6. Grid square:
7. Waypoint:
8. Name of carcass location: KAMBA SPRING
9. Sector name: CHEWORE NORTH
10. Description of carcass location: On mopane woodland
11. Carcass age: Fresh (0-3 weeks) Recent (3-52 weeks) Old (more than 1 year) ✓ Very old (more than 10 years)

A2


12. Cause of death (tick selections and provide details)

| Unknown | Natural or management | Illegally killed ✓ |
|---|---|---|
| | Disease | Automatic gunfire |
| | Problem animal control | Single action ✓ |
| | Drought | Shotgun |
| POACHED | Accident | Poisoned |
| | Predation | Speared |
| | Other: | Pit trap |
| | | Other: |

Please provide details on what led you to this conclusion: Bullet wounds on skull

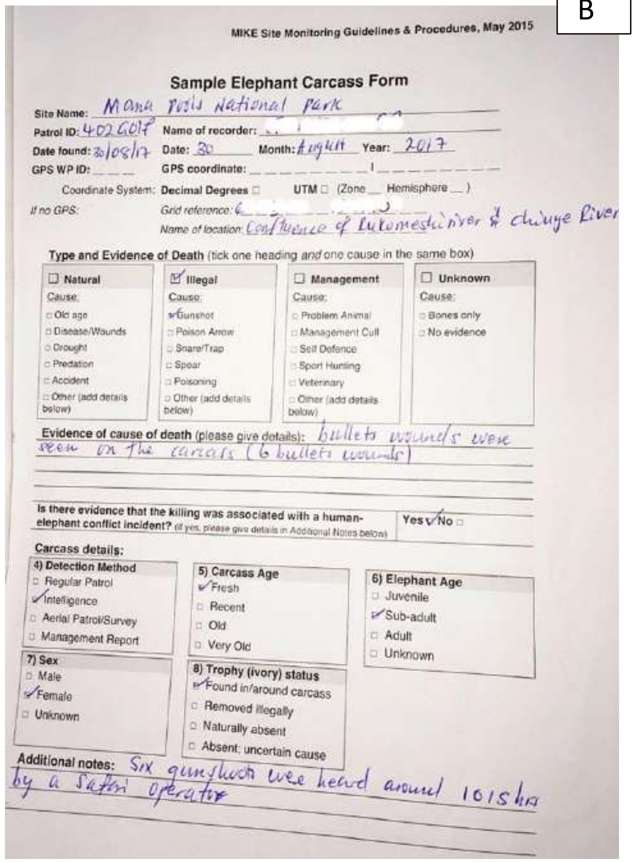
Please indicate the motivation for the illegal killing: Ivory removed, signs of axe chopped the tusks — Ivory ✓ / Bushmeat / Elephant/human conflict / Non-specific / Other:

13. Tusks:

| Were the tusks retrieved by the recording team | | | If not, were they: | Left | Right |
|---|---|---|---|---|---|
| Yes | Left | | | | |
| | Right | | | | |
| No ✓ | Left | ✓ | Left intact on carcass | | |
| | Right | ✓ | Chopped out | ✓ | ✓ |
| | | | Pulled out | | |
| | | | Naturally absent | | |

14. Tusk measurements: fill box under 18 with field measurements and fill remainder when information made available
15. Sex of carcass: Male Female Unknown ✓
16. Age-class of animal: Juvenile (0-8 years) Sub-adult (8-16 years) Adult (more than 16 years) ✓ Unknown

B


MIKE Site Monitoring Guidelines & Procedures, May 2015

Sample Elephant Carcass Form

Site Name: Mana Pools National Park
Patrol ID: 402 GOF Name of recorder:
Date found: 30/08/17 Date: 30 Month: August Year: 2017
GPS WP ID: GPS coordinate:
Coordinate System: Decimal Degrees UTM (Zone Hemisphere)
If no GPS: Grid reference: Name of location: Confluence of Rukomechi river & Chiruye River

Type and Evidence of Death (tick one heading and one cause in the same box)

| ☐ Natural | ☑ Illegal | ☐ Management | ☐ Unknown |
|---|---|---|---|
| Cause: | Cause: | Cause: | Cause: |
| Old age | ✓ Gunshot | Problem Animal | Bones only |
| Disease/Wounds | Poison Arrow | Management Cull | No evidence |
| Drought | Snare/Trap | Self Defence | |
| Predation | Spear | Sport Hunting | |
| Accident | Poisoning | Veterinary | |
| Other (add details below) | Other (add details below) | Other (add details below) | |

Evidence of cause of death (please give details): bullets wounds were seen on the carcass (6 bullets wounds)

Is there evidence that the killing was associated with a human-elephant conflict incident? (If yes, please give details in Additional Notes below) Yes ✓ No

Carcass details:

4) Detection Method: Regular Patrol; ✓ Intelligence; Aerial Patrol/Survey; Management Report
5) Carcass Age: ✓ Fresh; Recent; Old; Very Old
6) Elephant Age: Juvenile; ✓ Sub-adult; Adult; Unknown
7) Sex: Male; ✓ Female; Unknown
8) Trophy (ivory) status: ✓ Found in/around carcass; Removed illegally; Naturally absent; Absent; uncertain cause

Additional notes: Six gunshots were heard around 1015 hrs by a Safari operator

**Figure 5.4.** Examples of completed MIKE forms used by rangers in Mana Pools and Chewore to record elephant mortalities. A1 and A2 constitute the older form style (used 2009-2016), while B shows the condensed version (used from 2017). GPS locations and ranger names have been removed.

*Rangers' appreciation for the broader value of monitoring data*

Interviews revealed several possible reasons for poor ranger engagement with monitoring, including the time it takes to record data in the field, limited capacity to use devices like GPSes, and the feeling that data recording devices were tracking ranger performance. A deeper, and perhaps more prominent, reason for poor engagement is a low level of appreciation for the broader purpose of data collection. Whilst rangers value data collection as an important duty to their supervisors, they tended not to value data for its own sake and tended not to see its broader importance for management. Rangers stated that they received minimal feedback on how the data they collect was used by site supervisors. *"I can't lie to you…Since 2014 I have not had any feedback"* (ranger 1). Yet many rangers were eager to know more about how their data were used: *"We are the ones who collect, so we want to know, the data we are collecting, where is it going and how it helps us?"* (ranger 9). This desire for knowledge and feedback might be explained by the need for rangers to feel that their work is important and that they are doing it well: "*Feedback is very very important; it shows that you are doing something very nice…it will show that the information I am bringing is vital*" (ranger 16). Rangers described how being more actively involved in managing and using the data they collected would motivate greater effort in data collection:

> *"It's good to also know how to enter the same data into the computer…this will give you a passion to, you know, do it [field data collection] very very accurately since you will be the one who will enter the data. Also, that ranger who provides the information should be able to analyse, to explain what is happening pointing on the map, not just the supervisors. At the end of the day…you will see [understand] what you were doing in the jungle [field]…so your effort will be more."* (ranger 23)

> *"Rangers should know these things [how data are used]…so that they do it in a good way…if they don't have that information, one can leave the carcass without recording.*" (ranger 21)

Nevertheless, out of deference to their supervisors, some rangers did not expect feedback: *"On that one I don't mind… that is all up to him [my supervisor]...I can't say to him 'why you are not using my information'"* (ranger 12). Overall, rangers appear to face a tension between simply fulfilling data collection as a duty, and a desire to know more and be involved in the full data cycle:

> *"Now for me I am OK…I collect exact data from patrol and give to our officers here, I am happy to just collect the data. And also, to know everything also, from the computer and how to send the data...I just want to know, I am interested."* (ranger 20)

Although most rangers expressed mixed sentiments, a fair proportion expressed the sentiment that they would be more engaged with their data collection duties if they knew more about how the data they collected were used (Fig. 5.5). Many rangers desired more involvement in the full ranger-based monitoring and management cycle. *"They [supervisors] must teach us that information we keep for the reason A, B, C [management procedure]. Then I know when I see another carcass I can come and report with a punch because I know what I am doing"* (ranger 17). The potential gains from a greater awareness of the value and use of data amongst rangers may be significant. Rangers variously said that greater awareness would lead to *"more precise and more focussed*" monitoring (ranger 18), *"with a punch"* (ranger 17), that is carried out *"very very accurately"* (ranger 23). Supervisor interviews suggested, however, that they themselves do not always buy into data-driven adaptive management and may prefer to use personal intuition and institutional memory as a guide: *"Graph or no graph, I know my area"* (supervisor 1) (see Chapter 6 for more on manager perspectives).

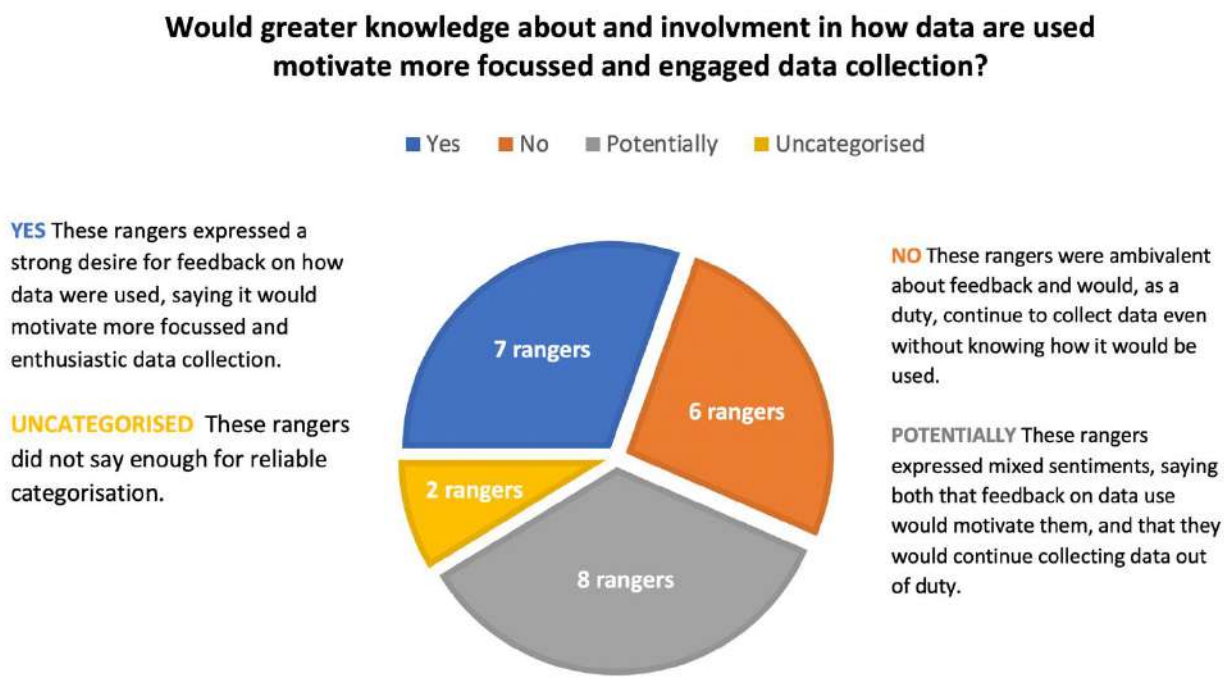



**Figure 5.5.** Based on their answers to several questions, the 23 ranger respondents were assigned to four categories based on whether greater involvement or knowledge of how data were used for conservation management would likely motivate more engaged data collection.

The strategic use of individuals can help catalyse an ethos of ranger ownership of data collection and monitoring. During the research, I identified several individuals that I refer to as "data champions", who I define as those who took active ownership of monitoring and had the potential to engender a greater appreciation for the value of data among the wider ranger group. Feelings of ownership of ranger-based monitoring and management must start at higher levels, however, as one supervisor remarked: *"Without them [supervisors] being interested, I don't think the rangers will be. You cannot force someone to do what you are not doing"* (supervisor 9). Another supervisor with significant previous experiences as a ranger demonstrated a particularly deep appreciation for the value of data:

> *"Some rangers do not appreciate the use of data…so when you tell them to collect data in the field, they end up compromising the whole lot because they don't see the value of the data. They don't understand the actual essence of data collection. We need to involve them [rangers] in whatever we do so they can start to appreciate the data collection."* (supervisor 9)

As an example of a data champion, this supervisor organises weekly individual sessions with rangers to train them in data entry and show them maps and graphs of the data they collect. Rangers may also have an important role as data champions. One ranger was given responsibility for managing the *SMART* data management system at his station and he felt strongly about the value of data for management, an attitude he wanted to inspire among other rangers:

> *"When new things come into place [SMART]…there is that resistance…but if someone of their rank is doing it and then explains to them, they really understand. If you know the importance of the data, then you have to be more precise and more focussed. When we started this SMART thing, rangers thought these guys wanted to monitor their movements, but then I explained that we need this data for us to get donor funding and for us to go to CITES to argue for the process of selling ivory…and now they [rangers] are starting to appreciate it."* (ranger 18)

Another ranger had experience with patrols and monitoring for 11 years and had recently become involved with data management. His experience suggested rangers may become apathetic about data collection if they do not see tangible outcomes:

> *"If you send someone to do data collection at the end of the day you have to come back and say, 'Oh with that data you have collected I have come up with such and such...'. If they don't see a tangible outcome, they will focus only on law enforcement and leave this monitoring."* (ranger 21)

Next, I examine how ranger occupational culture might intersect with this mixed engagement and appreciation for monitoring.

*The occupational culture of rangers*

I identified three specific elements of the broader occupational culture of rangers that influenced ranger engagement with monitoring: (1) a strong sense of duty and service, (2) deference to authority, and (3) rangers understanding their defined role in the organisational hierarchy. These are interconnected; rangers see their duty as fulfilling their defined roles within the organisation and as a way of serving their supervisors. These three elements permeated interview responses. While they do not comprehensively describe the occupational culture of rangers at my site, they did have a significant bearing on rangers' stated motivations and behaviours (especially in relation to monitoring but also more generally; Table 5.3).

*Rangers have a strong sense of duty*

Rangers demonstrated a strong sense of their responsibilities within the organisation, and a desire to fulfil them: *"I will do any duty assigned to me"* (ranger 8). The most commonly reported motivation for rangers' work could be summarised simply as "*That is our duty"* (ranger 9).

> *"I have a feeling that I need to finish my goal. I need to catch the poacher…I'm just interested in doing my job, the results I get motivates me."* (ranger 22)

Rangers described their dominant duties as (1) monitoring and reporting on illegal activities: *"I will keep on collecting data for them [supervisors], that is my job"* (ranger 10), and (2) defending wildlife from poachers: *"We are here to conserve, so that no one is going to disturb our animals*" (ranger 20). Rangers saw their duty as to their supervisors, their organisation, their country, to future generations, and to their God (Table 5.3). A sense of duty repeatedly emerged in a variety of discussions, from the purpose of patrols and data collection, to the challenges and motivations of being a ranger (Table 5.3). The notion of duty was closely tied to deference to authority, particularly that of on-site supervisors. This points to the second identified dimension of ranger occupational culture: A strong motivation for rangers to fulfil their duties is pleasing their supervisors and others above them in their organisation.

> *"I make sure everything is in order on behalf of my supervisor…I do good things for my supervisors, for the department, and for the country. If I do wrong, I do wrong for everyone up the ladder."* (ranger 14)

*Rangers defer to authority*

Questioning supervisors may occasionally happen but is mostly considered inappropriate: *"According to the military...it says that the seniors come first, and the juniors follow...if you say jump, I will jump."* (ranger 9). Rangers were mostly content with occupying the base of the organizational hierarchy: *"We are the foundation of the organisation as rangers, that makes me enjoy my job"* (ranger 14). While supervisors were often authoritative and commanding, there was variation among camps in the ranger-supervisor relationship. One supervisor, for example, espoused service leadership: *"To be a leader does not mean you know everything…I am happy to learn from junior staff"* (supervisor 4). Rangers perceived this supervisor as exceptionally kind and were motivated by his consideration. The role of the character of supervisors in influencing ranger motivation was more generally evident: *"The sort of response we get from the management team whenever we have got some problems… that gives me more appetite, that motivates me for my duty."* (ranger 16). Some rangers, however, complained of negative judgement from their supervisors, *"We need a leader not a judge…who listens to us, who asks: 'Give us your point of views'. Not just someone who says, 'do this'"* (ranger 1). While ranger responses indicated a respect for and deference to hierarchy, rangers themselves sought respect and recognition by their supervisors: "*The bosses must appreciate and say, 'ah guys you are doing a good job'…we need thanks each and every time. For example, if you are staying with your children, when the children doing nice for you, we say 'thank you very much'"* (ranger 17).

*Rangers understand their defined role within the organisational hierarchy*

Rangers had a strong sense of their defined place in the organisational hierarchy, as distinct from their supervisors. This is tied to their sense of duty: rangers understood that they were responsible mainly for patrolling and reporting findings, and their supervisors were responsible for planning deployments and anti-poaching strategies. *"I do my part, he [the supervisor] has got his part, each one has got his role"* (ranger 6). Whilst rangers actively participate in verbal patrol brief and de-brief meetings, sharing their opinions and concerns, they are generally content with leaving the development of management strategies to supervisors. One ranger used a powerful analogy, comparing the separate roles of rangers and supervisors to separate roles within a family:

> *"Like in your family there are some things like 'this is for father, this is for mother, this is for children'...if I play my role [collect data from the field] it is enough."* (ranger 14)

The defined role of rangers, and their responsibility to their supervisors, is reinforced by on-site supervisors: *"I am a senior ranger; my duty is to instil discipline. Before deploying I sit with the rangers and then I will tell the guys the role they should play in field. What they should do and what they must not do. Then we sign a form, so that we agree that the guys will do their duty"* (supervisor 7). I now examine how the above aspects of ranger work and culture influence data collection practices.

*Key elements of ranger occupational culture shape engagement with monitoring*

The three elements of ranger occupational culture identified above help explain how rangers approach and perceive data collection, the importance they ascribe to it, and their level of awareness of and involvement in stages after data collection (Table 5.3; Fig. 5.2). I began this work with the expectation that the level of understanding and appreciation of the value of data amongst rangers would correlate with their level of engagement with ranger-based monitoring. A notable outcome of interviews is the strong theme of data collection as a duty, together with the abovementioned calls for more active ownership of the data management and use cycle.

Rangers perceive data collection as a fundamental duty, to which they ascribed a high level of importance. The majority of rangers' time is spent on patrol, with rangers describing the monitoring of illegal activities as the main purpose of patrols. In this context, a sense of duty is central: *"Whilst you are in patrol you specialise on finding animals and illegal activities, I enjoy it because it's part of my job…I have to."* (ranger 9). Rangers also take pride in their role as the 'ears and eyes' on the ground: *"They use our information…because we are the right people on the ground"* (ranger 12). Relatedly, rangers considered data collection to complement their anti-poaching role: *" When I am collecting data it can lead me into apprehending a poacher or knowing how the poachers are moving"* (ranger 13). Reporting data collected on patrols to their supervisors, especially illegal activities, is a primary way that rangers demonstrated fulfilled duty: *"As a duty as a ranger, you would go out on patrol and bring something from the field to show you have done your job"* (ranger 12). This attitude is re-enforced by supervisors:

> *"We have standard operating procedures for anti-poaching and data collection. We came up with standing orders…it will force rangers to love data collection…everyone who goes on patrols, they have to collect data…when they come back they have to tell us what they collect."* (supervisor 7).

While the ranger-based monitoring and management cycle involves multiple stages after data collection – office data entry, reporting of data to regional and national levels, data analysis, and finally the use of data to inform management and patrol strategies (Fig. 5.2) – rangers' involvement in this cycle is limited, and tends to end with data collection. Rangers nonetheless have a good basic understanding of why they are required to collect data (Table 5.2):

> *"Data collection is needed in the field. It will be used for management purposes. If I go out and don't collect information, [the supervisors] won't know what is there. So, data collection is very important. You can't keep deploying people to where there is no animal sightings."* (ranger 22)

The most commonly mentioned reason for collecting data was to identify poaching hotspots: *"The carcasses within the area are the indicators of hot areas"* (ranger 13). A few rangers described the value of data as a tool for measuring anti-poaching performance: *"By looking at the carcass numbers you can see this year we have received a defeat…and look at the factors which have contributed to your failure, was it a shortage of manpower?"* (ranger 16). Yet rangers tend not to know the details of how their supervisors use monitoring data: *"I just pass the data through to my supervisors. Maybe they are the ones who do that [manage the data]"* (ranger 10). Rangers generally see the management of data, and its use for future deployments, as the responsibility of supervisors: "*We can give the information to our bosses, so they know where to deploy us"* (ranger 2). Whilst rangers did have a good basic understanding of why animal sightings and illegal activities were important to report for anti-poaching purposes, they generally did not know the details of how supervisors used these data and tended to see stages after collection as beyond their remit. Yet, even though many rangers were not aware of how the data they collected on patrol were used by their supervisors, they still engaged with monitoring as a fundamental duty. The duty and deference elements of occupational culture identified here are crucial in explaining this discrepancy. Recording illegal activities and animal sightings while on patrol was seen by rangers as an important duty to fulfil and reporting such observations to their supervisors was one of the main ways they demonstrated a job well done.

This suggests that data collection would continue even in the absence of a deeper appreciation among rangers of its broader purpose, as long as supervisors provide clear imperatives and instructions for it. Indeed, the greater consistency in the reporting of MIKE elephant carcass data versus regular patrol data (Figures 3 and 4) might reflect a clearer imperative and set of instructions to rangers in the case of MIKE data. Nevertheless, a fair proportion of rangers reported a desire to know more about how the data they collected were used, saying it would motivate more focussed and enthusiastic data collection (Fig. 5.5). The insights of the 'data champions' also suggested that a greater appreciation amongst rangers for the value of data was crucial to engaging them more effectively in monitoring and highlighted the possibility of compromised data collection in the absence of such an appreciation. On balance, my results suggest that whilst a sense of duty can motivate data collection to a certain extent, the quality (consistency, detail, etc.) of data (though not measured here) is likely to be improved when rangers appreciate the purpose of these data.

**Table 5.3**. Interview quotes illustrating (A) three elements of the occupational culture of rangers emerging from the interview responses, and (B) how these influence the level and nature of engagement of rangers with monitoring.

| DUTY AND SERVICE | DEFERENCE TO AUTHORITY | KNOWING THEIR DEFINED ROLES |
|---|---|---|
| **(A) As key elements of the occupational culture of rangers** | | |
| *"When you come here, you forget to think about everything else, I just focus on doing my work"* (R9) | *"I don't want to lie. I want to tell my bosses exactly what I did on patrol"* (R20) | *"We don't choose as rangers…we are given areas to go by supervisors"* (R3) |
| *"If I conserve elephants, I do it for the whole country, and for younger generations"* (R14) | *"If the big bosses are here…we are not alone, we are not lost…his presence makes a very good motivation to rangers…we can follow that"* (R5) | *" They [rangers] are the ones who are always on the ground, they are the ones I send on patrol to gather information about any illegal activity"* (S3) |
| *"We have to protect our heritage…that's what I know…that's what I feel".* (R1) | *"I make sure everything is in order on behalf of my senior ranger"* (R14) | *"It is their [supervisors] duty to compile reports for station level and report to higher levels"* (R14) |
| *"Adam was given a duty by God to take care of everything...this is the same job we as rangers were given to look after our wildlife"* (R23) | *"I cannot tell him [supervisor] what to do...It is only I need to do what he wants me to do"* (R12) | *"We have to learn from somebody, some people are strong, I need to follow them"* (R12) |
| **(B) As key factors influencing ranger engagement with ranger-based monitoring** | | |
| *"We are happy to bring back the information [data from field] because that is our duty"* (R2) | *"I want to play my side and give my bosses exact information I get from patrols"* (R20). | *"We collect the data, and we pass it onto our supervisors. Then they send it to their superiors at the regional level."* (R10) |
| *"That is an operating procedure ...whoever is in the bush will be looking for those things [signs of illegal activity] ...and informing the office"* (S1) | *"I don't know...the information will help them to supervise us…the supervisors know more…I am not sure how they use that information"* (R19) | *"I have never seen those MIKE carcass forms.…maybe our seniors do that…what we do is just give them the loc stats [GPS location of elephant carcass]"* (R10) |
| *"Both sides is so good, monitoring and also some anti-poaching. Both is important, because we are here for that purpose"* (R17) | *"We sit down, and I tell them to make sure they collect the correct carcass information "* (S4) | *"It [data] will help us to know even the hotspots, then this will make our superiors decide how to do our patrols, where to deploy"* (R23) |
| *"Yes it [ranger-collected data] helps management, it is our duty"* (R20) | *"During briefings I always emphasize to guys [rangers] to collect as much information as possible"* (S5) | *"Monitoring carcasses is a big part of my job…because I have to see everything that is happening in my area"* (R2) |
| *"That is our duty to monitor and report [poached] carcasses for management use"* (R22) | *"If we come back from the bush with no results, the supervisors can say 'Ah…that guys not going for the bush, just going to the bush and sleeping'"* (R17) | |

*Creating an enabling environment: ranger job-satisfaction and resource/capacity needs*

In addition to these three elements of ranger culture at my study site, my interviews and observations highlight how the work and living conditions of rangers also help shape engagement with monitoring. For example, rangers spoke extensively about job satisfaction and well-being. A love for nature was the most common reason rangers cited for enjoying their jobs: *"My love for these wild animals motivates me to be a ranger"* (ranger 7). While this motivated a desire to protect nature, for many rangers it also had a strong intrinsic element of enjoying nature for its own sake:

> *"To start with I love nature…that's the drive that can motivate me. Spending nights in the bush…the sounds of the birds…the sounds of lions…to live with nature, I like that."* (ranger 15)

Tied to this love of nature was an eagerness to learn: *"I enjoy mountain climbing…discovering hot springs, new type of trees and stones…everything is fascinating"* (ranger 10). *"I like to be a ranger because I learn lots from what I do, you can learn that long back people used to live here, you can see pieces of clay pots"* (ranger 20).

This love for nature and fascination with learning contrasted with the many challenges rangers faced. The most commonly described challenge was living away from family. The ranger stations are far from the nearest towns, and the need for schooling means that most families live away from rangers, some in distant parts of the country. Family separation had clear negative psychological effects, such as stress and worry:

> *"I want to share with my [spouse] or share with my children when there is a problem, but we are living apart so sometimes I get stressed and a high blood pressure."* (ranger 17)

> *"Sometimes you get bored, you need your partner to be close to motivate you…and see your child growing up. You get stressed… your mind will be centred there [with family], so your duties will be very difficult."* (ranger 18)

Living in remote areas means limited leisure opportunities: *"It is quite challenging to stay in the bush…if you go out there [trips to town] you can meet friends and you will be happy and when you come back you will be ready to do your work"* (ranger 16). Having no respite from the workplace also had implications for rangers' perspectives and relief from work duties: *"If we had a vehicle to play a soccer match in the community, it could help us take our mind off patrols"* (ranger 18). Harnessing the parts of their work that rangers enjoy, while minimising the challenges they face, is likely to lead to a more enabling environment in which rangers work more effectively (Moreto 2016a; Belecky et al. 2019.; Spira, Kirky and Plumptre 2019).

Adequate resources and capacity for monitoring also emerged as an important theme. Regardless of rangers' interest in data collection and use, if they are not appropriately resourced it can be challenging for them to fulfil their duties. Where the three elements of occupation culture identified here have deeper implications for ranger-based monitoring, resource and capacity challenges had more direct, immediate, implications. Patrol and camping equipment, communications tools, and vehicles were all limited at the case study site. *"So far, we have got shortage of equipment, like tents, GPSes, Cybertrackers, batteries..."* (ranger 8). Notably, a number of rangers reported having to purchase their own tents and resorting to cheap options: *"We have to buy our own tent because of the economic situation. I had to pay $40. I bought one with bright colours…poachers, they will see it."* (ranger 14). This had consequences for morale: *"If we can get these things [equipment and vehicles] our morale will be more"* (ranger 5). One supervisor felt strongly about this: *"I think the best motivator is to equip the ranger with enough apparatus to use in data collection"* (supervisor 7). A lack of equipment may also compromise data quality: *"If the information is to be clear…needs lots of equipment on the ground"* (ranger 14). Both field and office resources are necessary for proper data management, as one supervisor highlighted:

> *"We need batteries, GPSes, computers in order for MIKE to be moving smoothly. There are no batteries for the GPSes…how can I collect data?"* (supervisor 4)

Vehicles were identified by rangers and supervisors as the most important resource for general operations, yet most stations had only one vehicle and small fuel budgets. Rangers also said that vehicle limitations significantly reduced patrol coverage, and hence the accuracy and breadth of data collection. Rangers commonly said they felt they did not have adequate capacity for monitoring and that they would like more training, specifically in data collection (e.g., how to properly record elephant carcass data, how to use mobile devices such as *Cybertrackers*) and data management (e.g. the use of *SMART* software). *"I have to be educated to enter the data on the computer"* (ranger 1). *"I feel we need more and more training"* (ranger 5). While SMART training workshops are offered through local NGOs, these are infrequent and involve few rangers. Those that did attend training reported that they found these mostly useful. However, some complained that training sessions were difficult to follow: *"I didn't understand what was the database and what was the data model…it was short period over which he did all these things…I was entering data but not completely understanding"* (ranger 5). One older ranger was not keen on learning how to use a computer, however, saying *"[I will] leave for the younger guys to play with the computers"* (ranger 16).

## 5.4. Discussion

*A theory of change for improving engagement of rangers in data collection and monitoring*

Drawing on my results and existing literature, I develop a theory of change for engaging rangers more meaningfully and effectively in data collection. A theory of change describes how an initiative or intervention achieves its stated goal, or the particular assumptions, steps and outcomes between the particular initiative and the final goal (Stein and Valters, 2012). The theory of change identifies two *drivers of engagement* and two *enabling conditions* for achieving the overall goal of more meaningful engagement of rangers in monitoring. I see the achievement of this goal as itself contributing towards more effective species and habitat conservation through adaptive protected area management (Fig. 5.6). I first discuss two main drivers of ranger engagement with data collection. These are:

1. *The occupational culture of rangers*: particularly a strong sense of duty, deference to authority, and knowing their defined role within the organizational hierarchy.
2. *Seeing the value of data*: understanding the broader purpose of data (how it is used) motivates data collection.

These two drivers may be thought of as distinct sources of motivation for effective data collection, and I argue that both are important to understand and engage if the goal of effective and sustainable ranger-based monitoring is to be realised. The importance of each of these motivations, and how they might be encouraged, is discussed below.

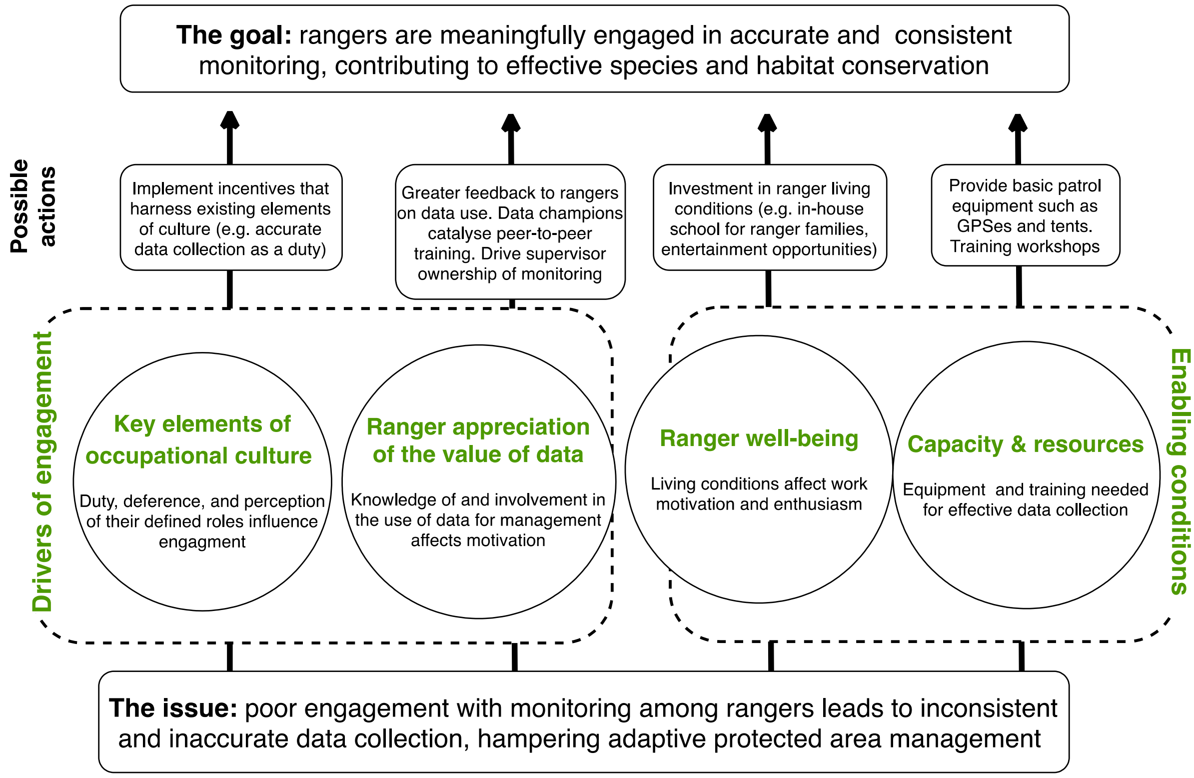



**Figure 5.6.** A theory of change for more meaningful engagement of rangers in ranger-based monitoring, highlighting key drivers of engagement and additional conditions that enable/disable such engagement. Possible actions to leverage these drivers and enabling conditions and achieve the overall goal are also indicated (these are only illustrative and more focussed action development is recommended).

*Engaging ranger culture*

The elements of ranger occupational culture identified here are crucially important because of how embedded I observed them to be within the ranger community in the Zambezi Valley. Interventions to better engage rangers with ranger-based monitoring will work best if they are sensitive to these aspects of existing occupational culture, and have incentives that work with, and not against, them (Fig. 5.6). An important implication of the strong themes of duty and deference is that recognition of the work that rangers do, particularly from their superiors, is essential to their motivation. Results indicate that rangers were eager to work well for their supervisors, and hence were encouraged when their good performance was valued and rewarded. This may be as simple as a 'well done' from the supervisor. A survey of 570 rangers across 60 sites in Africa, for example, demonstrate that '*little or no recognition as a professional'* was one of the most commonly cited answers to the question of what the worst aspect of rangers' jobs was (Moreto, 2016b). A key strategy for engaging rangers more effectively in ranger-based monitoring is to recognise good practices, such as a high volume or quality of raw data collected, consistent GPS recording of patrol routes, or a clearly written patrol report. This might be in the form of simple verbal affirmation and encouragement, the award of a good service certificate, notching towards promotion, or even recognition in the form of monetary incentives.

The themes of duty and deference identified here begin to shed light on rangers' attitudes towards, and practices of, monitoring, as well as what motivates rangers to work, how they perceive their occupation and what is and is not important within it, and how they see themselves within their broader organisational hierarchy. Rangers in this case study knew their place within the organisational hierarchy. We see this in other conservation contexts as well. Clear hierarchies and authority structures are common within the law enforcement and conservation agencies that rangers work for globally. In a study of ranger occupational stress in a Ugandan protected area, Moreto (2016) found that rangers felt the pressure of needing to please supervisors: *'Even you get pressurized, eh? And think that if they (management) come and find illegal activity near my area, then they might think that I am not doing [...] work'.* A multi-site study in South Africa similarly describes an organisational hierarchy of a section ranger at the top, who 'has command' over rangers in the rank of corporal and sergeant, through to lower level field rangers (Warchol & Kapla (2012). One of the authors of this current study (FM) confirms similar working dynamics in Mozambique (unpublished observation), while others describe similar working hierarchies in the USA (Charles 1982). Dynamics of authority and deference can likely be traced to the paramilitary training that many rangers receive at Mana-Chewore (two weeks of such training was mandatory for all rangers at this site). Such training is becoming increasingly common for rangers (Duffy et al., 2019).

*Fostering a greater appreciation of the value of data*

I find the rangers' appreciation for the value of the data they collect to be important for two main reasons. First, most rangers interviewed expressed a desire for feedback on how the data they collected were used, with seven expressing clearly that this would create strong incentives for engaged data collection in the future (Fig. 5.5). Of these seven, three 'data champions' expressed the desire (and showed the potential) to influence other rangers to appreciate the broader value of data, through peer-to-peer training (Fig. 5.6). Secondly, interview responses suggested a deeper level of appreciation of the value of data is likely to affect the accuracy and consistency of data collection, where ranger culture alone may not. While my data does suggest a sense of duty alone can motivate data collection, data also suggest that this will not guarantee consistency and accuracy in data recording. If the requirement is simply to report data, there may be no incentive to report accurate, consistent and comprehensive data (e.g. rangers may become selective in what they record and how they record it). Furthermore, such an approach may not be sustainable because it relies on supervisors continually enforcing the imperative to collect data. Authority structures and division of duties mean that the ranger-based monitoring and management cycle itself is divided, with little interaction and feedback between the collection of data by rangers and the use of these data by supervisors. Data champions were the rare exception. There is a danger that rangers will not take ownership of data collection if they don’t understand its broader purposes. This might lead to rangers prioritising other duties for which the broader purpose is clearer, such as anti-poaching operations and less on biological monitoring (see for example Warchol & Kapla, 2012).

The appreciation for data might also drive higher levels of engagement in the international MIKE programme. Office hardcopy and computer records of patrol observations at each station show that data on elephant carcasses were the most clearly and consistently recorded (compared to other illegal activities and animal sightings). With the MIKE programme, rangers are given specific instructions for what to record when encountering an elephant carcass and are then required to report this for data storage. Moreover, rangers are aware of how this data fits into and contributes towards a bigger objective at the local, national and even global level. One senior ranger highlighted the excitement of rangers when he told them how the elephant carcass data they collect are used to make international decisions concerning ivory trade. Research on ranger-based monitoring across eight sites in India similarly emphasises that data collection has potential to empower and motivate rangers if regular feedback on monitoring results is given (Stokes, 2010). One strategy that could contribute towards fostering greater data appreciation is active feedback workshops in which managers (or representatives of external bodies like MIKE) explain to rangers how field data are used, thereby giving rangers the sense that their data is making an important contribution.

Knowing how data are used not only ties into sentiments of wanting to be recognised as a professional, but to a sense of pride among rangers in fulfilling their various services to society. My observations of this are mirrored amongst rangers in other contexts as well (Spira, Kirkby

& Plumptre 2019; Charles 1982). In a study of the job satisfaction of rangers in Uganda, for example, Moreto, Lemieux & Nobles (2016) found that rangers saw their work as serving future generations and supporting national development by conserving wildlife. This sense of service was a key factor determining their job satisfaction. Helping rangers understand how their day-to-day data collection and monitoring fits into a bigger local, national, and even global picture and decision-making, such as is the case with MIKE, can help foster a greater appreciation for data collection and more effective collection and monitoring practices.

Engaging the elements of ranger occupational culture identified here and fostering a greater appreciation for the value of data amongst rangers will depend on good site-level leadership from supervisors. Indeed, my results indicate that good leaders have the potential to motivate rangers. Interventions and innovation should therefore be directed at both rangers and their supervisors.

*Enabling conditions for ranger-based monitoring*

In addition to understanding the drivers of engagement in monitoring, my results highlight the importance of both ranger well-being and the availability of capacity and resources as conditions that enable effective monitoring. Moreto (2016a) showed how a challenging work environment for rangers in Uganda contributed to occupational stress, with implications for work enjoyment and performance. Spira, Kirkby and Plumptre (2019) describe difficult living conditions, poor salaries and limited promotion opportunities for rangers in the DRC as key drivers of low job satisfaction and motivation. My results similarly reveal significant challenges faced by rangers (such as separation from family and a lack of stimulation outside of patrols), with rangers describing direct implications for their levels of motivation and focus in fulfilling their duties. Relatedly, rangers frequently reported a shortage of basic equipment for both patrols and data collection, describing how this made their work difficult and sometimes impossible to fulfil. The aforementioned global survey of rangers found that only around half of the 7100 rangers survey felt that they had sufficient basic equipment to carry out their duties (Belecky et al., 2019). It follows, then, that strategies to foster more effective ranger-based monitoring (e.g., by engaging the two drivers of engagement emphasized in this study) may not be successful unless the broader well-being of rangers and their basic resource and training needs are adequately addressed.

Being a case study of one area at one time, this study is limited by its temporal and spatial scope. It is thus difficult to generalise to rangers globally, or even in Zimbabwe. However, occupational culture as a way of thinking about the beliefs, values and motivations of rangers is generalisable to other contexts. Moreover, my results fit into a body of existing literature that highlights similar aspects and characteristics of ranger culture, perceptions and attitudes concerning their work. Given this congruence, I demonstrate the value of occupational culture as a lens through which to understand the engagement of rangers in the data collection and data use stages of ranger-based monitoring. In this regard, my case study does provide analytical generalisability in the sense, described by Yin (2009), of generalising to a theoretical position, which I summarize in the Theory of Change. Drawing on my own results and existing literature on ranger attitudes and working environments, this Theory of Change identifies key drivers of engagement and enabling conditions as levers for improving the effectiveness of ranger-led data collection and monitoring, and thus for conservation and protected area management. Further generalisability of these conclusions and the robustness of this Theory of Change requires further research with rangers in other contexts.

*Conclusions*

Many governmental and non-governmental initiatives seek to promote adaptive protected area management through the implementation of sophisticated data collection, management, and analysis protocols (Malpas and D´Udine, 2013; Stokes, 2010). However, the on-the-ground day-to-day reality of data collection for rangers may be very different. Drawing on research with rangers in my study area and existing literature on ranger motivation, occupational culture and attitudes, I developed a Theory of Change towards improving the implementation and outcomes of ranger-based monitoring. Specifically, I demonstrate how a more thorough understanding of key elements of the occupational culture of rangers and fostering the appreciation of the value of data among rangers and their supervisors could act as motivators for more effective ranger data collection. I also complement recent work on the lived experiences of rangers by highlighting well-being and adequate resources as necessary enabling conditions for effective data monitoring.

This study began with the assumption that the motivations and values of rangers have significant implications for conservation interventions that depend on rangers as key actors and are therefore worth investigating. My findings contribute to a small but growing literature on the social dimensions of the ranger occupation (Moreto et al., 2015; Spira et al., 2019). I reveal particular elements of the occupational culture among rangers in Mana-Chewore that influence engagement with monitoring: a strong sense of duty and service, deference to hierarchy, and clearly defined occupational roles. As discussed above, these findings complement existing research on the topic. Understanding this culture was essential to properly contextualise and indeed assess the importance rangers ascribe to data collection and the nature and level of their engagement in the broader data-based management cycle.

Rangers are at the frontline of conservation practice and protected area management globally, in the sense that they are directly involved in the practical implementation of interventions to protect nature. This includes anti-poaching and law enforcement operations, but also extends to duties such as baseline monitoring and evaluation (Stokes, 2010), and park-community relations (Moreto et al., 2017). It follows that the success of conservation management in many contexts is closely tied to the performance and meaningful engagement of rangers. Furthermore, engaging ranger perspectives and lived experiences is necessary to ensure a just working environment, which is necessary both from an ethical and a pragmatic standpoint.

# Chapter 6. Costly and unprofitable: park manager perspectives on data-based adaptive management of elephant poaching in Zimbabwe

## 6.1. Introduction

Globally, public funds are often stretched and are needed to address diverse and pressing challenges from poverty to climate change, so funding for biodiversity conservation is often limited. It is therefore imperative that available finances are invested wisely in actions that are likely to succeed. Within conservation management, there is an increasing emphasis on ‘evidence-based conservation’ - taking actions that are well-grounded in evidence (Gillson et al., 2019). Adaptive management (whereby ongoing monitoring data are used to evaluate management interventions with uncertain outcomes) is a technically well-developed and widely promoted way of using evidence to inform biodiversity management decisions. Despite this, there are very few examples of its successful implementation (d’Armengol et al., 2018; Serrouya et al., 2019). In this Chapter, I investigate the extent to which park managers in my study site in Zimbabwe use ranger-collected data on elephant poaching to inform their management actions, and the factors driving the extent to which adaptive management practices are adopted.

Adaptive management is a poorly defined concept within environmental management (Gregory et al., 2006). It was introduced over 40 years ago (Holling, 1978; Walters and Hilborn, 1976) as a process of ‘learning by doing’, and since then has come to mean a wide variety of things. Its key elements are a management goal, different management strategies available to achieve the goal, uncertain ecological and social responses to management actions, ongoing monitoring to measure management outcomes, and changing of actions where necessary (Keith et al., 2011). In its purest form, active adaptive management involves active experimentation with management actions (using controls and treatments) and learning by observing the outcomes (van Wilgen and Biggs, 2011). Passive adaptive management, on the other hand, involves a simpler process of implementing management actions, monitoring outcomes, and then revising actions based on these outcomes (Keith et al., 2011). In this

Chapter, I will focus on the extent of adoption of the latter (passive adaptive management) among park managers at my study site (Fig. 6.1).

Much literature laments the frequent failure of adaptive management in the real world. The disparity between adaptive management in theory and practice may reflect a failure to account for the complex social and institutional contexts in which adaptive management is implemented. Keith et al. (2011) highlight conflict among stakeholders, institutional complexity, and disagreement between scientists and managers as key impediments to adaptive management. Walters (2007) describes various proposed monitoring and adaptive management programmes within fisheries management that were ultimately never implemented. Strong individual leaders who buy into monitoring and evidence-based management were identified as key to the few cases of successful implementation (Walters, 2007). Danielsen et al. (2005), reviewing 15 case studies of locally based monitoring, conclude that another key success factor is the degree to which monitoring is institutionalised within local management structures (e.g. featuring in job descriptions). Nuno et al. (2014) further identified the importance of institutional barriers and influential individuals in the failure of adaptive management of bushmeat hunting in the Serengeti. Further, practitioners such as park managers are influenced by numerous socio-political factors in addition to baseline evidence (Adams and Sandbrook, 2013). Importantly, managers may not take ownership of monitoring programmes if they do not see their broader value and relevance in the context of their other priorities (Cundill et al., 2012).

These case studies reveal that quantitative monitoring results are not always meaningful to, or well-integrated with, the daily activities of park managers. For example, the decisions made by a protected area manager with a limited budget, a small and under-resourced contingent of rangers, and a range of ever-changing threats, are likely influenced by more than just data. The relationship between evidence and policy may be messier than much of the evidence-based conservation literature acknowledges, further emphasising the need to understand how social factors interact with evidence to shape decisions (Adams and Sandbrook, 2013). It is important to understand the pressures and limitations that local managers face, and their priorities, in order to identify how ranger-collected data can be more sustainably integrated within their decision-making processes.

Ranger-based monitoring of elephant poaching presents a model case study of monitoring and adaptive management in biodiversity conservation. Measuring changes in poaching through space and time is essential to evaluating the effectiveness of conservation policies at reducing elephant poaching, whether global or local (e.g. legalising international trade or intensifying local ranger patrols; Moore et al., 2018; Hauenstein et al., 2019). Accordingly, the Convention on the International Trade in Endangered Species (CITES) established the MIKE programme (Monitoring of the Illegal Killing of Elephants) in 1997. There are now 60 MIKE sites across Africa at which rangers collect data on elephant carcasses encountered during regular patrols. The database currently houses over 19 000 carcass records (CITES Secretariat, 2019). The MIKE programme aims to provide baseline elephant poaching data to inform both international ivory trade policy and local elephant management at MIKE sites (see Methods section for more detail).

Here I use the MIKE programme, and particularly its local implementation in the Mana-Chewore MIKE site in northern Zimbabwe, as a case study of factors that influence the use of monitoring data in management. My overall aim is to identify the factors that determine the extent to which local park managers have adopted adaptive management. I define adaptive management in this context as the systematic analysis of trends in ranger-collected data on elephant poaching (i.e., MIKE data) to evaluate anti-poaching strategies and improve these strategies through a process of learning from data (Fig. 6.1). The MIKE programme is not in itself an adaptive management programme, but it does seek to promote the use of ranger-collected data to inform local management decisions (CITES Secretariat, 2019)

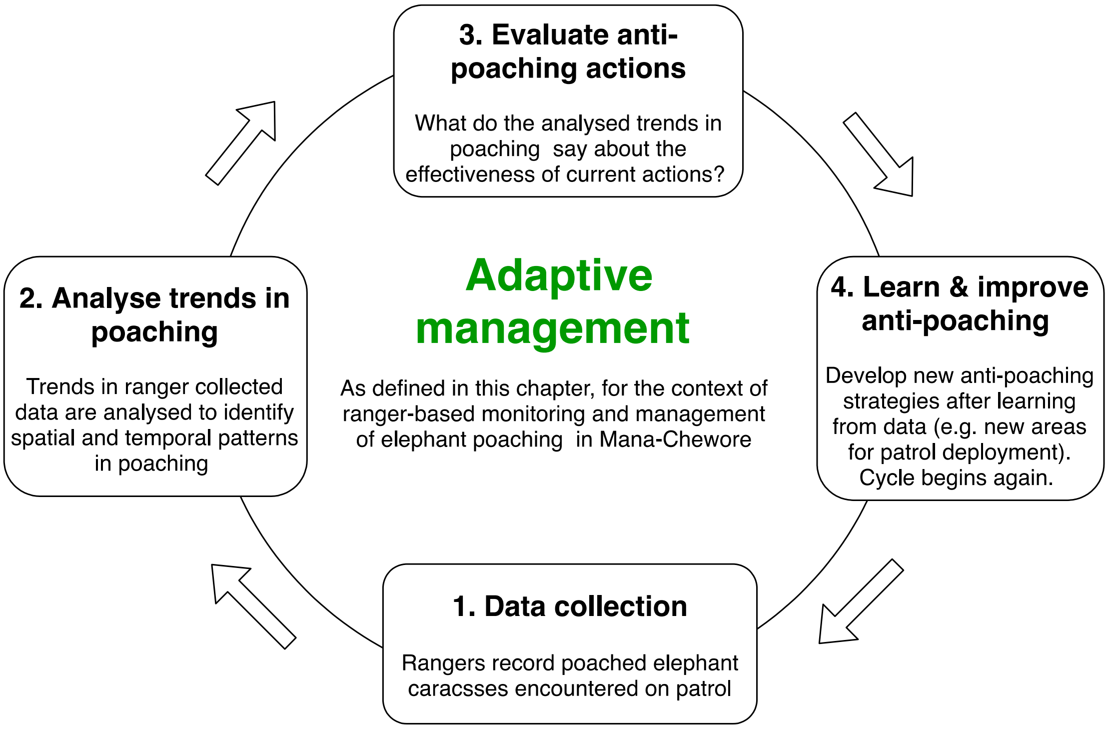



**Figure 6.1**. A conceptual diagram of the standard adaptive management cycle showing how it would apply in the context of ranger-based monitoring and management of elephant poaching in Mana-Chewore. The overall aim of this chapter is to determine the extent to which such a management cycle is adopted by park managers in Mana-Chewore.

To address my overall aim, I use semi-structured interviews with three stakeholder groups: (1) Park managers directly involved in planning and implementing the monitoring and management of elephant poaching in Mana-Chewore; (2) Key informants involved in national-level elephant management in Zimbabwe (mostly senior staff of the Zimbabwe Parks and Wildlife Management Authority; hereafter Zim Parks); and (3) Senior staff of the MIKE programme, responsible for administering MIKE at the regional and global levels. I pose the following focussed research questions:

1. How do park managers in Mana-Chewore currently use ranger-collected data on elephant poaching (i.e., MIKE data), and why?
2. How do park managers perceive data-based adaptive management – that is, the evaluation and improvement of management actions based on systematic analysis of ranger-collected poaching data?
3. To what extent have park managers adopted data-based adaptive management, and what factors most influence the extent of adoption?

4. What do (a) national-level respondents involved in local elephant conservation, and (b) senior staff of the MIKE programme, perceive as the main drivers of adaptive management adoption (or lack of it) in Mana-Chewore?

To answer these questions, I integrate interviews with the three stakeholder groups identified above with extensive personal observations and informal discussions conducted during two month-long field visits to ranger stations in Mana-Chewore (August 2018 and July 2019). I use my findings to  develop a theory-of-change that outlines key priorities and actions to promote effective use of ranger-collected data to inform anti-poaching strategies in Mana-Chewore. This theory-of-change draws on technology adoption theory (Venkatesh et al., 2003), and the concept of human-centred design (Steen, 2011), to ensure that solutions take as their starting point the perspectives, concerns, priorities, and decision-making context of park managers.

## 6.2. Methods

*The MIKE programme in Mana-Chewore as a case-study of adaptive management*

My Mana-Chewore case study site is one of the official sites of implementation of the MIKE programme (see Chapter 2 for a full description and map of the site). The official aim of the MIKE programme is to "*provide information needed for elephant range States and the Parties to CITES to make appropriate management and enforcement decisions, and to build institutional capacity within the range States for the long-term management of their elephant populations*" (CITES Secretariat, 2020). This may be divided into an international policy aim and a local elephant management aim (Malpas and D´Udine, 2013). Regarding the former, poaching data from multiple MIKE sites are reported to the sub-regional level (e.g., southern Africa) and then the continental level. Data are then aggregated to identify continental trends in elephant poaching for presentation at key international wildlife trade policy meetings (such as the Conference of the Parties to CITES) in order to help inform international decisions about ivory trade and anti-poaching policy (CITES Secretariat, 2019). The successful fulfilment of this aim depends strongly on consistent and reliable reporting of elephant mortality data from the 60 MIKE sites across Africa (CITES Secretariat, 2019). However, the MIKE programme also intends for the elephant mortality data recorded at each site to inform "*appropriate management decisions*" at the site level, and to build capacity for local elephant management.

Thus, while MIKE is not an adaptive management programme in itself, the adaptive use of baseline poaching data to inform management strategies is implicit in its goals. In their comprehensive review, Malpas and D´Udine (2013) concluded that MIKE had performed well in terms of informing international policy, but has largely failed to contribute effectively to local elephant management. They concluded that, across a representative set of MIKE sites, ranger-collected elephant poaching data are not well integrated with local anti-poaching decisions. In response to this, MIKE evolved to include more of an emphasis on supporting local anti-poaching efforts at a smaller number of key MIKE sites though the 2014-2018 programme: "*Minimizing the Illegal Killing of Elephants and other Endangered Species*" or MIKES (CITES Secretariat, 2018). My Mana-Chewore case study site was selected as one of eight of these higher priority MIKES sites, for which a key stated goal was "*Law enforcement, adaptive management and monitoring systems, protocols and capacity are strengthened in high priority protected areas*" (CITES Secretariat, 2018). Furthermore, MIKE has partnered with local NGOs (Panthera and the African Wildlife Foundation) to implement SMART (Spatial Monitoring and Reporting Tool) in Mana-Chewore (Wilfred et al., 2019). Efforts have been made to integrate MIKE data recording within the SMART system (see in the results below that respondents often used MIKE and SMART interchangeably).

*Interviews and thematic analysis*

In July and August 2018, I conducted face-to-face semi-structured interviews with 9 park managers, and 17 national-level respondents involved in elephant management in Zimbabwe. Park managers were interviewed at four different ranger stations at the Zambezi Valley MIKE case study site in northern Zimbabwe (two stations in Chewore Safari Area and two in Mana Pools National Park). Managers were employed by the Zimbabwe Parks and Wildlife Management Authority (ZPWMA; hereafter Zim Parks) and all available park managers were interviewed during my visit to each ranger station. Park managers included "senior managers" who had ultimate responsibility for site management, and "wildlife officers" who shared management and ranger supervision responsibilities. Further details of manager participants are provided in Table 5.1 of Chapter 5). Manager interview questions covered several broad discussion areas: manager responsibilities and anti-poaching strategies; the collection, storage and reporting of elephant poaching data; and the use of these data for Park management. National-level respondents were key informants with particular knowledge and experience around local elephant conservation and the MIKE programme. Most of these participants (n=8) were senior staff of Zim Parks, who I specifically targeted as individuals responsible for or involved in the design and implementation of national anti-poaching strategies. Within the national-level key informant group, I also interviewed four leaders of local NGOs, two local academics, and three local wildlife consultants, all involved in some way with elephant conservation and/or the MIKE programme at my case study site. Finally, I interviewed four senior staff involved in the administration of the MIKE programme across Africa and globally, who were also familiar with the implementation of the programme in Zimbabwe. Interview guides for park managers national-level informants, and MIKE staff are included at the end of this Thesis (Appendices 3, 4, and 5).

Based on repetition of information and themes in interview responses, I judged that saturation (the point where additional interviews would yield little new information) was reached for each stakeholder group (Newing, 2010). Interviews were analysed using thematic analysis to identify patterns of meaning in the interview data in relation to the specific research questions (Braun and Clarke, 2006). As an example of what I mean by a theme, a prominent theme was that managers did not see how data-based management could improve their work performance. The importance of a theme was assessed by its prevalence both across several interviews, and within individual interviews, as well as by the extent to which it spoke directly to the overall research questions. In addition, a theme/factor was accorded higher importance if it was clearly important to a respondent. This was judged by tone of voice and emphasis, how early on in an answer to a particular question the theme/factor was mentioned, and repetition of the theme in several answers. For a detailed description of the interview and analysis procedures used, see chapter 5 (which used the same procedures) and the Thesis methods overview (Chapter 2).

*Supplementary field observations*

Interview data were supplemented with extensive personal observations during each station visit. These included observations of (a) the general work environment of managers (their office space, the operations room, maps on walls, availability and use of computers), (b) general management practices (patrol briefings and debriefings, staff roll call), and (c) various management documents (patrol brief and debrief forms, elephant carcass record sheets, patrol observation record books, etc). Also, at three of the four stations, I spent 1-2 hours familiarising myself with the computer databases used to store and manage ranger patrol observations (under the guidance of a ranger/manager at each site).

## 6.3. Results

**Note section numbering is used for this results section (unlike elsewhere in the Thesis) to aide in the categorization and flow of results.*

To provide context for my main findings, I first present an overview of (a) ranger-based monitoring of elephant poaching in Mana-Chewore, and (b) the responsibilities and anti-poaching strategies of park managers. I then present results on how managers currently use ranger-collected data on elephant poaching, concluding that data use is short-term, basic and reactive. The next section focusses on the main result of this study – the factors explaining why there is only limited adoption of systematic data-based adaptive management by park managers in Mana Chewore (summarised in Fig. 6.5).

*1. Overview of ranger-based monitoring of elephant poaching in Mana-Chewore*

Ranger patrols in Mana-Chewore typically involve a group of 3-4 rangers and last for 6 nights, with rangers deployed by vehicle to a particular location where they set up a temporary camp. Rangers patrol out in different directions each day before returning to camp. Less commonly, rangers may move camp every 2-3 nights. While on patrol, rangers collect a wide variety of biodiversity and threat data (such as large animal sightings and evidence of poaching). These data are typically recorded manually (using a pen, notebook and GPS device) or, more recently, using handheld mobile devices loaded with *Cybertracker* software. Patrols are preceded by a 1-hour briefing at the main station, during which supervisors (park managers) describe the purpose of the patrol, and the protocols to follow. After the 7-day patrol, rangers are picked up by vehicle and then a de-brief session is held at the main station in which rangers report on the patrol to their managers. Notable observations (such as evidence of illegal activity) are reported, and future actions to take based on the patrol are discussed (e.g., whether to patrol the areas again). Elephant carcasses are occasionally encountered and recorded as per the procedures above. Given that Mana-Chewore is a MIKE site, extra emphasis is placed on accurately recording elephant carcass data and all stations had either a soft or hard copy database of historic records of elephant mortality. Following MIKE guidelines (MIKE Programme, 2015), rangers record details such as the cause of death (poached or natural mortality), age and sex of the elephant, and the age (state of decomposition) and location of the carcass. A full description of data collection and reporting procedures at Mana-Chewore is provided in chapter 2 of this Thesis.

*2. The life of a park manager: responsibilities and anti-poaching strategies*

*2.1. Park manager responsibilities*

Park managers described a breadth of responsibilities. These included many that were not directly related to anti-poaching and ranger supervision: (1) Mobilizing, managing and allocating resources (vehicles, fuel, patrol equipment etc.); (2) Drawing up, managing, and reporting on budgets; (3) Supervising and compiling standardised situational (daily), weekly, monthly and annual reports to send to regional and national offices; (4) Liaising with local rural communities around conservation awareness; (5) Maintaining stakeholder relationships (with professional hunters, private ecotourism operators, local NGOS, and sport fisherman); (6) A variety of practical management tasks including road maintenance, fire management, invasive species control, game capture and translocation, and problem animal control; (7) Attending within-organisation meetings at the regional and national offices; (8) Attending stakeholder strategy workshops (e.g. elephant management workshops); (9) General management of the ranger contingent, including welfare, skills and training, timetabling of ranger duty cycles, and maintaining general discipline; (10) Visiting remote ranger bases (temporary and permanent); (11) Supervision of general maintenance of buildings and infrastructure (offices, staff quarters, radio connectivity, solar power, internet connections, etc.).

Alongside these wider duties, park managers carried out various activities directly related to anti-poaching, including: (1) Developing patrol strategies (areas to target, patrol length and type, ensuring adequate coverage, monitoring key natural resources like water availability, etc); (2) Supervise the area and timing for patrol deployments (which are usually carried out by a senior ranger either by vehicle or boat); (3) Ranger supervision (briefing rangers on patrol strategy and goals, training rangers in anti-poaching strategies, leading patrol de-briefs); (4) General anti-poaching strategy development and evaluation (see below for a list of current strategies); (5) Liaising with community intelligence officers; (6) Reacting to poacher incursions; (7) Liaising with local police and judicial processes related to poacher conviction.

*2.2.Strategies used to reduce poaching, and information sources used to inform strategies*

Park managers described a number of strategies that they use to tackle poaching in Mana-Chewore. These included, in order of their importance (measured by how frequently and in what order each was mentioned within an interview): (1) Strategic deployment of patrols to poaching hotspots or points where poachers are known to enter and exit the park; (2) Specialised vehicle patrols ('mobile patrols') covering wide areas of the park for surveillance (these are 1-3 days in length and involve dropping off and picking up rangers for multiple rapid patrol legs over a wide area); (3) Setting up and ensuring constant manning of semi-permanent anti-poaching camps (there are 2-3 of these across Mana-Chewore positioned in key hotspot areas); (4) Intelligence gathering through community informer networks (in collaboration with the Department of Investigations within the organisation); (5) Community awareness and engagement (conservation education, and employment of local community members to incentivise conservation). Of particular note is the heavy dependence on external stakeholders (trophy hunting and ecotourism operators, and local NGOs) for the patrol-based strategies (1 and 2 above). In Chewore, hunting operators often provide a vehicle and driver for the deployment and collection of patrol units by vehicle (the main hunting camp is near the main ranger station). In Mana Pools this service is commonly provided by local eco-tourism operators who are based near the main ranger station, and also by a local NGO that provides a vehicle and driver.

The most significant source of information that park managers relied upon to develop their anti-poaching strategies was observations by patrols: *"we are guided by our data previously collected on patrols. Which areas to cover and why will be guided by past observations, observations of animals, poacher spoors, contacts with poachers, and [observations of] where there is food and water available for animals"* (manager 3). Data that provided insight on the behaviour of poachers was seen as the most useful: *"we need data to give us an idea of their [poachers'] concentration and activities"* (manager 2). A less common source of information that managers use is community intelligence; *"informants can tell us that a group of 5 poachers are planning to enter at this point"* (manager 1).

*3. How are elephant poaching data currently used in Mana-Chewore?*

*3.1. Data use is basic and reactive, with limited systematic trend analysis to evaluate anti-poaching strategies*

Park managers in Mana-Chewore use ranger-collected elephant mortality data in a variety of ways, the most common of which is to identify poaching hotspots (Table 6.1). Identification of hotspots was basic and qualitative, with the most common approach being the use of coloured pins marking carcass locations on a large map, *"our reports from ranger patrols are straight away pins on the operations map, showing carcasses and poacher activities"* (manager 9; see Fig. 6.3). When asked how he identifies hotspots, another manager said: *"I go through the old reports and find areas which are hotspots with many carcasses"* (manager 4). A senior staff member in the organisation said this is a common strategy: *"rangers are in the command centre and they ask, 'where did we cover and what did we get', then there is a map on the wall with the carcasses identified and the manager says, 'ah, there are more carcasses in this area.'"* (national level respondent 13). At all stations, there was no evidence of carcass locations being plotted using computer mapping software, nor was any predictive hotspot analysis conducted.

Patrol data on elephant mortality were typically used for short-term patrol to patrol decisions (Table 6.1), "*during the debriefing we will capture the information on what they have seen [e.g., a carcass] and the results of that patrol will then guide us to the next patrol*" (manager 5). This is typical of the more reactive approach commonly taken by managers on the basis of patrol data, "*we have deployed some people up there and they have seen a poaching camp, so based on that information we make a follow up to check if illegal activities are still happening in the area*" (manager 1). As one national-level informant remarked,
*"Currently management in the Zambezi Valley is reactive management, it's not adaptive management in the sense of being data driven*" (national level informant 15) .The use of data to track longer term temporal trends was far less common and, when it was mentioned, it mostly involved a general sense from the data as to whether poaching was increasing or decreasing (Table 6.1). One manager was not able to tell me whether there were seasonal patterns in the carcass data recorded over the last few years, suggesting that he does not routinely consider long-term trends in poaching data. Another manager (and this was the exception) had however plotted hand-drawn bar graphs showing monthly records of various illegal activities (Fig. 6.4).

**Table 6.1**. The different ways that park managers use ranger-collected data on elephant poaching in Mana-Chewore, based on interview responses and corroborated by personal observations. Illustrative quotes are shown, and forms of data uses are listed according to their importance to managers (as judged by how commonly each form of data use was mentioned during interviews, and how strongly each was emphasised when mentioned).

| Data use | Frequency | Quotes |
|---|---|---|
| Identify poaching hotspots | Very Common | *"Carcasses help show where the poachers' hunting grounds are"* (m3); *"I go through reports and find which areas are hotspots with many carcasses"* (m4); *"to know which areas are being poached"* (m5) |
| Inform patrol deployments | Very common | *"It influences our patrol patterns; you see animals are killed here so we deploy in those areas"* (m8); *"we deploy rangers…where most elephants are killed"* (m9) |
| Report to regional and national levels | Common | *"we send the carcass information on to regional and HQ [offices]"* (m5)<br>*"I send the [elephant mortality] information to my superiors"* (m4) |
| Track temporal trends in poaching | Occasional | *"helps to know is poaching increasing or decreasing and why?"* (m4); *"to know which season poaching is more or less"* (m5); *"we have seen poaching going down from 2016 to 2017"* (m7). |
| Flag need for more anti-poaching resources | Occasional | *"So that they [national headquarters] know what is happening on the ground and whenever we ask for resources they know where we are coming from"* (m7); *"HQ uses that [elephant mortality] information to allocate resources to us"* (m1) |
| Inform broader anti-poaching strategies | Rare | *"Carcass info helped in the placement of fly camps [temporary anti-poaching bases]"* (m5); "*We can make some decisions from those trends [in poaching]"* (m7) |
| Measure performance of anti-poaching | Rare | *"If you see every year you are recording more and more carcasses in an area…then you must know that your management plans are actually lacking somewhere"* (m6); *"It is a benchmark, an indicator of how much we are performing at anti-poaching"* (m8) |

Park managers rarely mentioned the systematic analysis of trends in poaching data, or the evaluation of anti-poaching strategies based on trends (Table 6.2). Across all interviews and site visits, there was only one instance of longer-term anti-poaching strategy being directly influenced by carcass data. Three respondents (managers 7 and 9, senior Zim Parks staff member 3) described how semi-permanent anti-poaching 'fly camps' were set up in 2017 in two areas where significant numbers of poached elephant carcasses, poachers' footprints, and poacher camps had been recorded over the previous 18 months. These camps were permanently manned by ranger rotations and the subsequent observed decline in carcass records in the park concerned was attributed to these camps: *"that was the major reason why poaching went down"* (manager 7).

In summary, the evidence considered here (interviews, informal discussions, and field observations from station visits) indicate that managers do value and use elephant poaching data, but data use tends to be (a) short term (patrol to patrol), (b) reactive (as opposed to predictive), and (c) non-systematic (no deliberate plotting and analysis of trends). This, combined with the fact that managers tend to rely heavily on intuition and experience when making decisions, means that the use of data to evaluate and update anti-poaching strategies (i.e., systematic adaptive management) is not embedded into park management (Table 6.1).

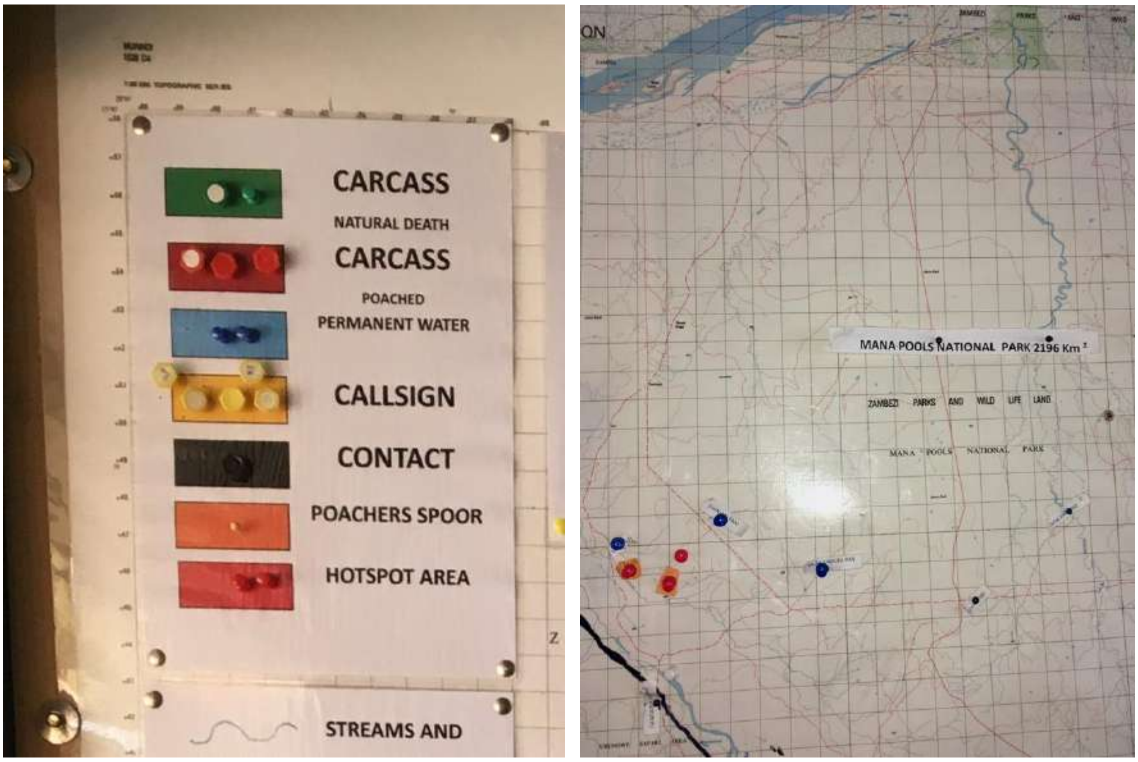
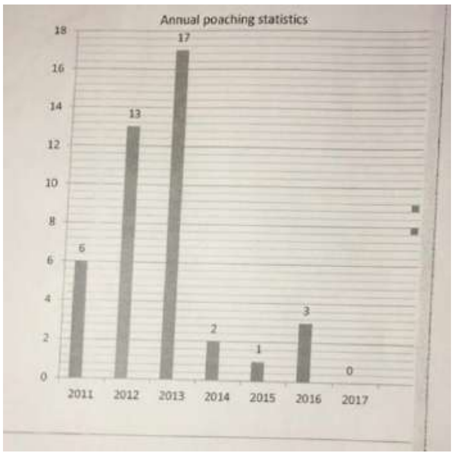



**Figure 6.3.** An operations map in the main office at one of the ranger stations in Mana-Chewore, showing the pins used to indicate the locations of notable observations (including elephant carcasses).

A




B

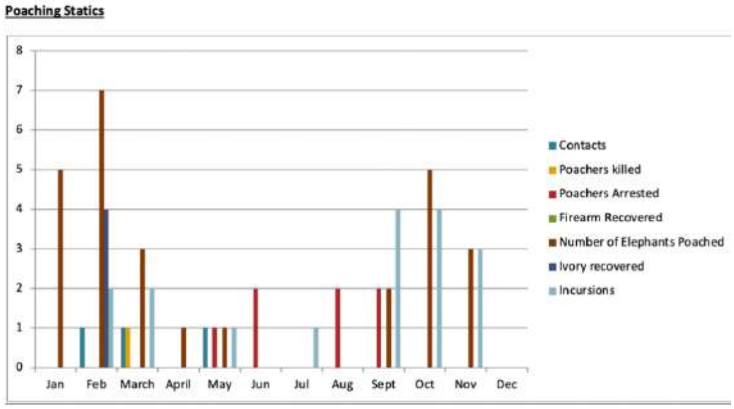



**Figure 6.4**. Across all interviews and field observations, these graphs represent the only two instances I observed in which managers/rangers in Mana-Chewore plotted or evaluated long-term trends in poaching data. (A) A graph on the office wall at one of the main ranger-stations, showing the annual trend in poached elephant mortalities recorded at that station. (B) A graph of poaching statistics within in a year, created by a ranger at another station who was delegated responsibility for managing poaching data.

4. *Park manager perceptions, and adoption, of the MIKE programme for monitoring elephant poaching*

Most park managers spoke positively about MIKE and were committed to collecting and reporting elephant mortality data, *"We have received it [MIKE] with both hands, because everyone is committed to have a database on elephant mortalities because that information will help for future planning" (manager 3).* Managers understood how monitoring could help them achieve their anti-poaching goals, *"MIKE is very important for us, we need to monitor protected species and reduce illegal killing in our area" (manager 4).* However, park managers in Mana-Chewore have adopted MIKE mainly as a programme for routinely collecting and reporting on elephant mortality data, not as a tool for using these data to inform their own management decisions. Thus, MIKE has been widely implemented, but not as a local adaptive management tool. Indeed, rather than highlighting the advantages of adaptive management, many managers described the benefits of MIKE in terms of donated resources, *"MIKE has made an impact on the conservation of wildlife here, we find people are trained, donations like the land cruiser, and other resources for data capturing"* (manager 1). The reasons behind the limited adoption of MIKE as an adaptive management tool, and the general limited level of adaptive management in Mana-Chewore, are discussed below.

*5. Why is there limited adoption of data-based adaptive management in Mana-Chewore?*

Why do park managers in Mana-Chewore tend not to systematically analyse trends in elephant mortality data to inform their anti-poaching strategies? Interview data and personal observations point to a number of factors limiting the adoption of adaptive management (Fig. 6.5). Perhaps the most prominent reason is that park managers simply do not buy in to systematic data-based management (they do not see the value that it adds). Another important and related reason is that adaptive management is largely externally driven and disconnected from local realities. Technical factors such as resource and capacity limitations also play a role, but these are less important to park managers and have perhaps been overemphasised in the past.

*5.1. Ownership: park managers do not buy-in to systematic data-based management*

There was little evidence that managers had taken ownership of data-based adaptive management in Mana-Chewore. While the MIKE and SMART programmes (both of which are designed to promote adaptive management) were widely implemented across the four ranger stations, this implementation was at the surface-level. Data were being collected and stored, but not utilised to inform management decisions. Managers have not taken full ownership of the data analysis, evaluation and learning aspects of these programmes. Interview data suggest that a significant reason why managers do not systematically analyse data to inform their decisions is that they have not bought into such an approach, and generally do not see how it is better than traditional practices based on experience and intuition (Fig. 6.5). As one national-level informant remarked:

> *"A good manager does not need MIKE [data-based management] to know if they are doing a good job. He lives and breathes the park. You have got these guys with experience and intuition. There is a danger of putting MIKE too high on a pedestal. It is not built into their management psyche."* (national-level informant 10)

One senior manager described ownership as a significant factor limiting the adoption of programmes like MIKE and SMART: "*the problem is management [park managers] should show interest, we have to show buy in and interest, otherwise things here will die a natural death*" (manager 3). When asked about his involvement with MIKE and SMART, another manager said:

*"I delegate some rangers to do that [manage SMART/MIKE data]…I am not involved myself"* (manager 2). I identified a number of factors that are important in explaining this low level of ownership, a primary factor being that the difficulties of adopting a data-based management approach currently outweigh the perceived benefits from a park manager's perspective (Fig. 6.5). There are several reasons for this:

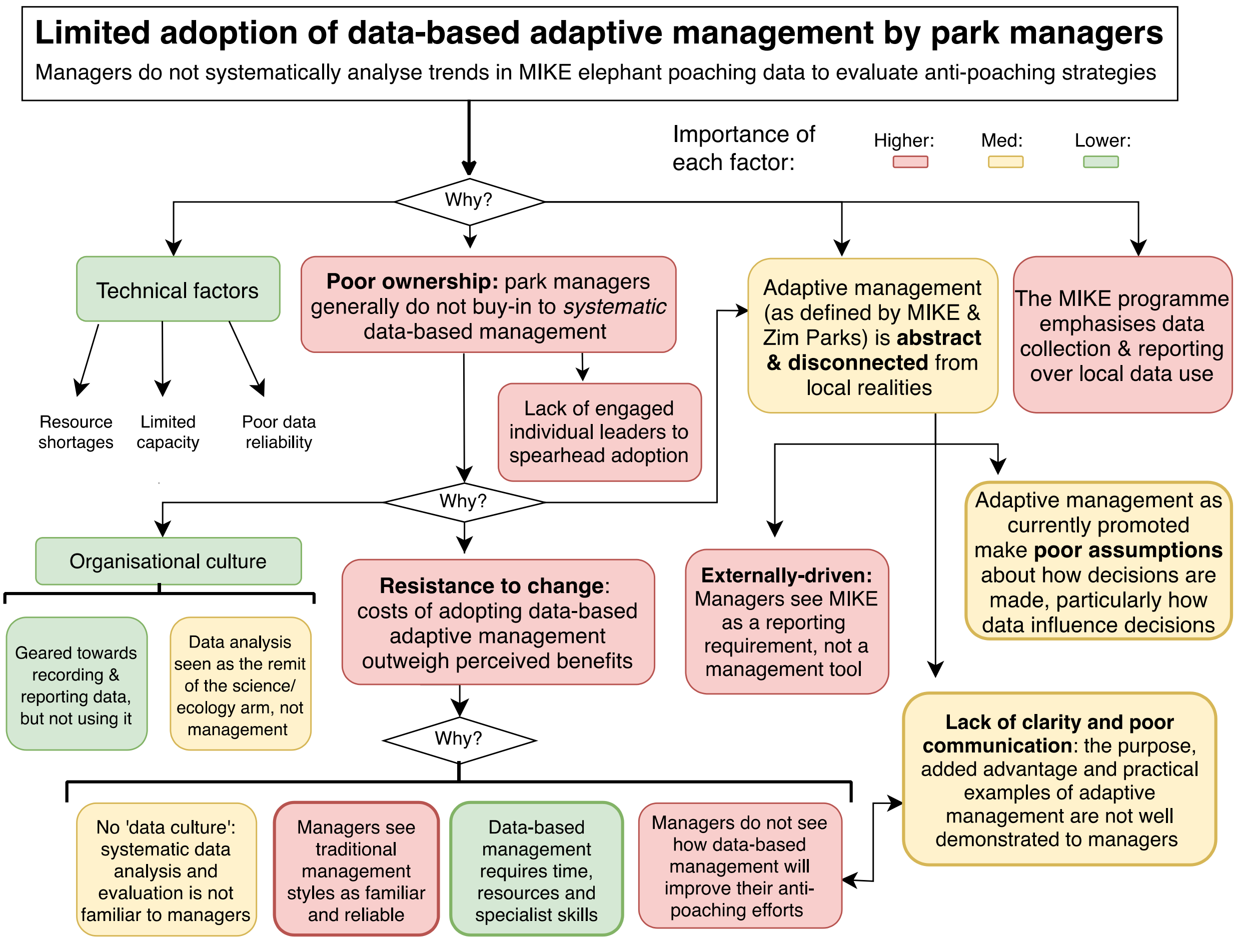



**Figure 6.5**. Factors explaining the limited adoption of data-based adaptive management by park managers in Mana-Chewore, based on analysis of interview themes. The evidence (interviews and field observations) to support each aspect of this diagram is provided in the main text. The three colour categories represent the importance that I ascribed to each factor in terms of determining the adoption of adaptive management, based on my overall assessment of interview data and observations. Importance categories mostly represent the importance ascribed to each factor by respondents themselves, but not always (e.g., some respondents were judged to overemphasize technical factors as described in section 5.4).

### *5.1.1. Lack of engaged individuals to spearhead adoption*

Many of the national-level informants emphasized engaged individual leaders within Zim Parks (at both the park and regional levels) as influential in the adoption of adaptive management.

"*If a regional manager has been deeply soaked in MIKE and the said 'hey guys, we need this', then that's when we would see value…leadership trumps everything*" (national-level respondent 10). When asked whether ranger-collected data were being used at the park level, another respondent remarked, "*I think it depends on the type of area manager, how proactive and analytic he is. For others [other managers] they just deploy [rangers on patrol] without using information*" (national-level respondent 14). National-level respondent 2 remarked that site-level leadership had an "*enormous influence*" on the effective implementation of programmes like MIKE and SMART and gave the example of an individual manager who showed particular initiative in training himself in computer skills and plotting monthly poaching data (this is the same manager described below, who produced the graph in Fig. 6.4A above). Another respondent remarked, *"MIKE requires a champion at the site who appreciates the value of data. The role of individual area managers cannot be overstated"* (national-level respondent 4). MIKE staff respondents similarly highlighted the importance of key individuals at the site: *"You need someone at the suite level who will actually look at the data and interpret it not only for reporting purposes but for management interventions"* (MIKE staff member 1); "It varies according to the manager…young managers appreciate the importance of data but some of the older managers are used to the way they do things in the past…they may not think data is important" (MIKE staff member 4).

### *5.1.2. Absence of a data culture: systematic data analysis is unfamiliar to managers*

Across nine park manager and national-level interviews, focussed discussions with rangers/managers responsible for curating computer databases of elephant mortality at each station, general observations during station visits, and several informal discussions with managers, I came across only two examples where elephant mortality data had been summarised or plotted in some way (Fig. 6.4). Evidence of systematic data analysis, and its contribution to management, was thus almost absent. One of the national-level respondents with significant experience within Zim Parks summarised this issue well:

> *"There hasn't been developed within the field management staff that if they are going to manage their areas properly, they need to collect information, analyse it, and evaluate their performance, and then improve it for the next year. How do you, within an organisation, develop a culture of learning and adaptive management? That simply is not happening." (national-level respondent 16)*

One respondent (manager 2), when I told him I wanted to ask him some questions about MIKE data, said he was happy to answer my questions as long as they were not too technical. This same manager did not have a computer in his office, and delegated responsibility for managing the MIKE database to two more technology-savvy rangers. It was clear he was not comfortable with data management and analysis. Another manager was interested to learn computer-based analysis, but felt unfamiliar with it, *"I tried to ask someone who knows much about computers to assist me, but no-one to assist. I am very interested, I would have all the analysis, but there is no one to teach me"* (manager 4). This was the only manager interviewed who expressed a clear desire to learn and employ data analysis. Given this unfamiliarity with data-based management, it is not surprising that managers currently much prefer more traditional management approaches.

### *5.1.3. Managers prefer traditional management styles, which are seen as reliable and familiar*

Most park managers have adopted a traditional style of management - that is, management based on experience, intuition, practical action and only very basic (reactive) data use. This has been the historic institutional standard and is considered familiar and reliable, so managers are resistant to change. One senior manager who had been actively involved in the recent implementation of data-based management systems (SMART and MIKE) in Mana-Chewore highlighted this resistance:

> *"Most people prefer to use what they are used to, like the map on the wall, unlike this SMART. These sophisticated tools take time…like when you are using a map in the office you can call in the rangers and show them where there is an incursion. But on a laptop, you will not all be able to see, people will not be able to contribute, we will not be able to react quickly. Like this recent incident with a fire, the guys on the ground radio me the co-ordinates and quickly I can see where they are on the map on the wall. But using a laptop, I cannot react quickly. I am not connected to Google Earth, I need to be trained how to use it, maybe the laptop batteries will go flat…"* (manager 3)

When I asked another manager to tell me which system he thought was better, he said *"I have a computer in my brain, I have been moving around my area since 2009. I remember the carcases and poachers spoor, I know where the hotspots are, the entry and exit points [of poachers]"* (manager 4). He was, however, willing to take on the new system, albeit alongside the old: *"To me I will go with both. I would rather keep two copies – one on the computer and one on my hard copy files. Even with new system I will keep going with the manual one. If you give me meat, I won't throw the beans away. There could be a virus on the computer, or it could be stolen, even a flash stick [memory stick] can be stolen"* (manager 4).

### *5.1.4. Managers do not see how data-based management will improve anti-poaching*

This preference for traditional management approaches is magnified by the fact that park managers generally did not see or appreciate the added value of data-based management, *"until they [managers] actually see how these systems improve what they do, they find it hard to buy into it"* (national-level respondent 15). One manager, when asked whether graphs of trends in the data would be useful for him, said:

> *"To date I have not used a graph and I have no problem with that. All the information that they get, that is fed into SMART, comes from me because I am the supervisor of the operations. It is me who initiates that data should be collected…then I look at the data…and then send the data to MIKE…so graph or no graph, I know what is happening in my area."* (manager 6)

As a senior Zim Parks staff member remarked: *"the acceptability of MIKE is not always there…managers do not appreciate the value of the information…it really requires someone who understands [data-based management]"* (national-level respondent 6).

### *5.1.5. Data-based management is too 'slow' in a poaching crisis, which requires reactive management*

Another reason why managers were sceptical about the value of data-based management (through systems like MIKE and SMART), was because they felt it was too 'long term' in that it does not address more immediate poaching concerns. One manager said, *"These MIKE things work when you are on general patrol, but when you are in hot* *pursuit of poachers…what we need is real time cameras that we can monitor from the office. MIKE is historic, MIKE is static, and you use the information as the history which assist you to solve the future problems"* (manager 8). Another manager expressed a similar sentiment: *"In my point of view…MIKE is just interested in carcasses and what have you…but as a manager I want to be proactive, not reactive…I want to reduce poaching…I want to observe and protect live animals…not carcasses"* (manager 2).

*5.1.6. Data-based management costs: time, resources and specialist skills*

Managers may not have the time and resources to invest in adopting new approaches and skills related to data-based management, especially considering their diverse and demanding responsibilities as managers (see Results section 2.1). Thus, managers commonly delegated responsibility for managing and reporting MIKE elephant mortality data to others, "*They [managers] have a workload with managing a protected area, so they focus their efforts somewhere else and delegate the MIKE thing to someone else"* (manager 9). Another manager said: *"I have a dedicated ranger in the office for that, I think they keep the data and also forward it to MIKE…am I correct?"* (manager 6). There is a disconnect here where managers don't see MIKE as an important management tool to engage with, but rather as a reporting requirement to be delegated. When viewed this way, recording and reporting MIKE data becomes a burden, *"If I was a manager, I would see MIKE's purpose as record keeping. It is a pain in the arse"* (national-level respondent 10).

*5.1.7. Organizational culture: data recording and reporting is strongly institutionalised, but data evaluation and use is not*

The absence of a strong data analysis culture amongst managers is linked to a broader organisational culture of meticulously recording and reporting data. During my station visits it became clear that data recording and reporting were strongly emphasized. I observed many hard copy files, forms and books for recording and storing data of various kinds (patrol observations, patrol briefing and debriefing notes, staff time logs, equipment registries, budgets, etc.). Alongside this, I observed at all stations a strong emphasis on regularly reporting these and other data to the regional Zim Parks office for the Zambezi Valley. These included daily, weekly, and monthly reports which included information on the status of vehicles, fuel and other resources, the status of staff, notable evidence of illegal activities, notable animal observations, and outcomes of trophy hunts (this list is based on a review of a selection of reports compiled at each station). On several occasions, I had to wait to interview a manager as they had a report to send. When asked what happens to elephant mortality data once it is collected, or how these data are used, most managers emphasised reporting these data to higher levels:

> *"When information is reported from the field, we record it down and report it to the main area manager. Most information we also provide to the higher offices…daily, weekly, monthly, quarterly and annual reports. To the regional and higher levels."* (manager 1)

> *"I send the data to regional offices because they ask for that information." (*manager 4)

> *"We are sending the MIKE data to the regional office, they are taking it up elsewhere, I am not sure where."* (manager 2)

On several occasions, it was difficult for me to get managers to talk about how elephant mortality data were used locally because discussions around the use of data would often focus on data reporting. More particularly, managers described reporting MIKE data to the resident ecologist, *"We have an ecologist who works in the area. When she asks for MIKE information, the rangers in the office will provide that MIKE data"* (manager 1). This is linked to the fact that data management and analysis within Zim Parks is seen as the remit of research, not management.

### *5.1.8. Organizational culture: data analysis is seen as the responsibility of the science/ecology section of the organisation*

Most managers felt that analysis of data was not their responsibility but rather that of scientists, or more particularly the 'ecologist' (the person employed by Zim Parks to carry out research to help management):

> *"I am not sure. You can get that information from the resident ecologist [an employee within the science/research section of the organisation]. That's purely*

*research…I am here to see nobody kills elephants and to make sure the rangers deter the poachers."* (manager 6)

*"I think the research guys has to do that, they have the responsibility to analyse the data, and then give us advice. If they need the data, we can provide it."*(manager 9)

Overall, data collection and reporting are considered the remit of managers and rangers, but data management and interpretation is the remit of the ecologist. As one senior Zim Parks staff member remarked: *"Management is responsible for collecting data because it is ranger-based, the resident ecologist is responsible for synthesizing the MIKE and other data"* (national-level respondent 12). However, a minority of managers recognised that they could work together with the ecologist on analysis, rather than leave it entirely to them: *"Analysis of data used to be research work, but us on management we could also do that…because we quickly need that information…we work hand in hand with ecologist"* (manager 3). Another manager described how analysing data might be easier for managers I they use SMART because they can analyse data with *"a click of a button"* (manager 8).

Section 5.1 has identified seven barriers to the adoption of systematic adaptive management in Mana-Chewore,  focussing on the perspectives of the people responsible for using data in management. The next section considers the problem from the perspective of the design and implementation of particular adaptive management programmes. From this vantage point, adaptive management has not been adopted because the programmes promoting it are externally driven and disconnected from local realities.

### *5.2. Adaptive management is abstract and disconnected from local realities*

An alternative way of framing the problem of limited adoption of data-driven adaptive management in Mana-Chewore is to consider the design and implementation of the programmes themselves. In particular, the current design and implementation of the MIKE and SMART programmes have failed to address the barriers identified in section 5.1 (such as park manager ownership).

*5.2.1. Adaptive management makes poor assumptions about how decisions are made*

An essential element of adaptive management is the connection between monitoring data and decision-making. Interview data suggest that the vision for adaptive management in Mana-Chewore (as promoted by MIKE, the NGOs helping to implement SMART, and senior Zim Parks staff) is not clear and, more specifically, abstracts and oversimplifies how managers make decisions and how ranger-collected data influence these decisions (Fig. 6.5). From a programme design perspective, there are two related problems with the current implementation of adaptive management in Mana-Chewore (through the MIKE and SMART programmes):

1. The assumption is made that if managers had access to data on poaching rates and trends, they would inevitably base their decisions on these data.
2. The context in which managers make local management decisions, and the various ‘non-data’ factors that influence these decisions, are not adequately considered.

The first problem leads to an emphasis on simply ensuring data are collected and available to managers and assuming that better decisions will naturally arise. A linear sequence of actions from data collection, through data analysis, to management decisions is assumed. This was reflected in interviews with MIKE staff, who emphasized the importance of making data available to managers in a usable format, *“it is our responsibility to provide [MIKE sites] with data in a usable format that’s accessible and easy to use”* (MIKE staff member 2). In this vein, the MIKE programme has recently been developing an online platform that automatically produces graphs and maps of the MIKE elephant mortality data submitted from each MIKE site, allowing local managers to log into the system and see their poaching data summarised. *“They can log in and see all their historic data up to the latest date, and we are hoping this will help them use the data more effectively for the site*” (MIKE staff member 1). Such a solution runs the risk of further establishing the externally driven nature of the MIKE programme (Fig. 6.5). It also depends on managers buying into data-based management in the first place.  Interview data suggest that managers are more likely to respond reactively to short term patterns in patrol data when making anti-poaching decisions, rather than base these decisions on systematic data analysis.

There are also numerous contextual factors, entirely unrelated to patrol data, that shape how local management decisions are made. Managers have extensive responsibilities and are therefore constrained by time, so may make decisions 'on the fly' based on their intuition and experience. Also, some of the strategies that managers use to reduce poaching (like community informants and community awareness campaigns) do not require analysis of patrol data. Limited resources may also constrain manager's decisions to undertake certain anti-poaching actions; limited ranger numbers and vehicles may mean certain actions are not possible (even when data suggest they are necessary). Finally, park manager relationships with their superiors at the regional and national level may influence how decisions are made.

### *5.2.2. The MIKE programme is externally driven*

Overall, managers saw the MIKE programme, managed by the international organisation CITES, more as a reporting requirement and less as a useful management tool. CITES requires that MIKE sites like Mana-Chewore report accurate elephant mortality data on an annual basis, to contribute to a broader database of continental poaching levels. This is not to say managers were not positive about MIKE or that they did not use elephant poaching data in some way for local management, but the emphasis was on fulfilling a reporting responsibility:

> *"Collecting elephant poaching data is now a donor and CITES requirement so we are forced to collect data. CITES is now like a silent supervisor."* (manager 3)

> *"Managers are not yet making use of MIKE data locally. They are doing it because they [people responsible for MIKE implementation] are beating theirs heads to get it out. I would be surprised if area managers put much value on this."* (national-level respondent 10)

Managers commonly associated MIKE and SMART with donations from outside organisations. A manager described the SMART data-based management programme as *"a requirement from CITES and donors, to give more funds*" (manager 3). These donations were often perceived as the primary benefit of these programmes; "*The landcruiser we got from MIKE was a big benefit"* (manager 3). Another manager saw the programme as an opportunity to get more resources: *"MIKE is good because it is showing us trends, but a major limitation is resources. It would be good to have one vehicle [donated] from MIKE every 10 years"* (manager 8). This sentiment was also held by some senior Zim Parks staff: *"We need more batteries, GPSes, and metal detectors…and a vehicle. Maybe MIKE could even provide a plane for us to do aerial patrols and cover more area"* (national-level respondent 5). These financial benefits motivated managers to comply with MIKE implementation and reporting requirements, as did the prestige that was attached to being part of a global programme, *"CITES is a reputable institution. Indirectly MIKE helps us get more funding from donor communities"* (manager 8). Both park managers and national Zim Parks staff also emphasized the importance of complying with MIKE requirements as a way of giving more legitimacy to their proposals at CITES conferences (Zimbabwe regularly proposes legalizing ivory trade), *"We actually gave reference to MIKE when we were lobbying [at the 2016 CITES conference], saying that we have our own MIKE sites"* (national-level respondent 12).

This has resulted in MIKE being implemented not so much as a management tool to inform local anti-poaching decisions, but as a reporting tool to fulfil external obligations. This lack of local ownership meant that some managers, rather than analysing MIKE elephant mortality data themselves, expected MIKE as a programme to give feedback on trends in the data. One manager informally asked me after interview why MIKE had not given feedback on the data he had submitted, *"We give MIKE all this data, and then what?"* (manager 2). Another manager said, *"MIKE should give us advice on how to manage elephants based on the data we submit to them"* (manager 9). Yet external organisations promoting the implementation of MIKE (CITES and local partner NGOs) see it as the manager's responsibility to make use of MIKE data to inform their decisions, *"It is ultimately the site's responsibility to use the data"* (higher-level MIKE respondent 1). This speaks to a broader issue in the design and implementation of adaptive management through MIKE and SMART: the broader purpose of this approach to management is not well communicated to managers. It appears that the expectations of the MIKE programme, as well as those of park managers, need to be better aligned.

### *5.2.3. The purpose and value of MIKE is poorly communicated to managers*

Many of the national-level respondents ascribed managers' lack of buy-in as at least partly to poor 'marketing' and communication of the MIKE programme to managers:

> *"Many managers may not even know why they are doing MIKE and why it is important. There needs to be more awareness raised among managers about*

> *MIKE. I think it is a tool that is very useful, but we need to embrace it, it needs to become part of us." (national-level respondent 11)*

> *"There is room for better communication on what MIKE is to stakeholders who might want to take it up. There is a need for marketing MIKE to officers on the ground as well as other strategic officers. Are the operations side [managers] aware of MIKES…do they embrace it?"* (national-level respondent 13)

When asked what the most significant barrier to the uptake of MIKE and SMART was, one of the more senior managers responded, *"I think an awareness campaign needs to be done to the managers, they are the very first people who need to be enthusiastic "* (manager 9). Notably, MIKE staff and senior Zim Parks staff spoke about adaptive management as a concept in abstract and general terms, but seldom provided examples of what it entails in practice. Greater clarity on the adaptive management element of the broader MIKE programme, and specific practical examples of how managers might benefit from systematically analysing data, would help make adaptive management less abstract and more connected to local realities (Fig. 5).

*5.3.The MIKE programme has emphasized data collection and reporting over the local use of data.*

Interview respondents involved in administering the MIKE programme regionally and globally acknowledged a tension between the programme's mandates of (a) informing international policy through representative poaching data from many sites, and (b) building capacity for local elephant management at individual MIKE sites:

> *"So yes, there is the global trend analysis with PIKE and then there is the capacity at the sites. For me, that [capacity-building] is the area we need to strengthen considerably…more regular trainings, more engagements with sites to give them support. Making sure they can use the MIKE data a bit better. The danger is that the sites do it [implement MIKE] as a compliance requirement rather than informing management at the site."* (senor MIKE staff member 1)

> *"The MIKE mandate is to inform the parties of the Convention [CITES] about levels and changes in poaching. That's kind of behind everything…I don't think the capacity building for sites to use MIKE information is something MIKE has done very well over the years."* (senior MIKE staff member 2)

MIKE staff members were eager to realise the mandate to inform local elephant management, but the way the programme has been implemented to date has involved a strong emphasis on getting sites to provide data and less of a focus on supporting local data use: "*There is a perception that we just take data, which we have, we just took data for many, many years and never, never gave anything back apart from a training to collect more MIKE data, which, you know, people love trainings, but I think it's pushing our luck a little bit*" (MIKE staff member 2). Capacity-building and support provided from the MIKE programme to particular MIKE sites has focussed on data collection, rather than supporting local adaptive management, "*The contribution of MIKE is to mainly build capacity to ensure that reliable and accurate information on elephant mortality is collected...that is the main thrust. Apart from enhancing skills, there is also a need to provide equipment to ensure the data is recorded accurately"* (MIKE staff member 3).

*5.4. Technical challenges: resources and human capacity*

Respondents in both Zimbabwe and at the MIKE level emphasised human capacity and basic resources as essential to the implementation of the MIKE programme and broader adaptive management (see section 5.1.5 above). *"There is a need to provide equipment and GPSes, so the data is recorded accurately"* (MIKE staff member 4). *"We need batteries, GPSes, computers in order for MIKE to work smoothly*" (manager 4). Limited capacity to use new technologies and to interpret data systematically was highlighted as a key constraint:

> *"It is also a challenge in Zim Parks…we have people who have field experience, but in terms of academics they are challenged…so it [MIKE] has to be packaged in a manner that speaks to the human resource capabilities of the people on the ground."* (national-level respondent 13)

> *"There are not many people in Zim Parks who were familiar with computers…he [the park manager] can read any small beetle and identify any spoor…but then you say you want digital information…you are asking too much."* (national-level respondent 14)

Yet these technical challenges are only part of the problem and may not themselves be driving the poor adoption of adaptive management in Mana Chewore, which previous sections suggest is more to do with poor ownership and abstract goals (hence the lower importance ascribed to technical factors in Fig. 6.5). As one respondent remarked, "*Technically the system works well, the biggest challenge is implementation and buy in*" (national-level respondent 15).

## 6.4. Discussion

Previous research has explored why the implementation of adaptive management fails in many real-world contexts, despite it being a widely advocated approach to environmental management. These studies have , variously, analysed single case studies of adaptive management (Serrouya et al., 2019; van Wilgen and Biggs, 2011), reviewed several case studies within a particular field of management (Keith et al., 2011; Walters, 2007), or provided a higher-level appraisal of adaptive management as a concept (Gregory et al., 2006; Lee, 1999). Missing from previous work, however, is direct investigation into the perceptions and values of on-the-ground managers themselves, who are ultimately responsible for adopting adaptive management. In this study I found that the attitudes and perceptions of park managers in Zimbabwe towards adaptive management strongly influenced the extent to which such an approach was adopted.

*Managers do not buy into data-based adaptive management*

Interview data suggest that perhaps the strongest reason for the limited adoption of data-based management by park managers is Mana-Chewore is that managers do not see how the approach is better than traditional management practices. Adoption theory, which examines the choice individuals make about whether or not to adopt a particular technology or innovation, is a useful lens through which to consider the reasons for these low levels of ownership. The innovation of adaptive management in this context involves both an idea (that of making decisions based on systematic data analysis), and tangible technologies (such as computers to analyse and summarise data).

Straub (2009) reviewed three dominant theories to explain the adoption of technology innovation (with a focus on school environments), concluding that adoption is a complex social and developmental process, as individuals form "unique but malleable perceptions of technology that influence their adoption decisions". He argues that in order to address poor adoption, the cognitive and emotional perceptions of end users must be carefully considered, as well as their broader work context (Straub, 2009). Park managers in Mana-Chewore expressed cognitive concerns about data-based adaptive management in that they were not familiar or comfortable with the idea of analysing data systematically, nor did they believe adaptive management would improve their anti-poaching efforts. As regards to emotion and affect, some park managers expressed anxiety about computer technology and analysis, while others felt frustrated that others (such as the ecologist or the MIKE programme itself) were not taking responsibility for analysing poaching data and giving them feedback. Also, the organisational and work context of managers hindered adoption of adaptive management. Mangers had limited time due to diverse work responsibilities and tended to favour reactive short-term management (using data from the last few patrols to inform the next). Also, their organisational culture, as well as the MIKE programme itself, emphasised the importance of reporting poaching data to higher administrative levels (e.g., regional and national offices within Zim Parks, and the regional MIKE office in South Africa), but not the actual use and analysis of data at the site.

A highly influential theory of adoption, which has been developed using empirical comparison of several adoption theories and refinement of their salient characteristics, is the *United Theory of Acceptance and Use of Technology* (UTAUT) (Venkatesh et al., 2003). The theory proposes four key determinants of technology adoption: (1) *performance expectancy* (the degree to which an individual believes the innovation will assist them in fulfilling their duties), (2) *effort expectancy* (the perceived ease of using the innovation), (3) *social influence* (whether or not an individual feels pressurised by important others to adopt the innovation), and (4) *facilitating conditions* (the degree to which an individual believes that there is an organisational and technical infrastructure in place to support the innovation). The UTAUT was particularly useful in helping to explain the limited adoption of systematic data analysis and adaptive management in Mana-Chewore (Table 6.2). Indeed, the four key determinants of adoption provide a complementary and parallel understanding of the drivers of poor ownership of adaptive management by managers identified from interviews. In a study of challenges around the adoption of the SMART ranger-based monitoring technology in a Tanzanian park, Wilfred et al. (2019) similarly found that users were not familiar with the technology (leading to a low performance expectancy) and did not feel they had the capacity to use it well (high effort expectancy).

**Table 6.2**. A summary of how the four key determinants of innovation adoption developed in the *Universal Theory of Acceptance and Use of Technology* (Venkatesh et al., 2003) help explain why park managers in Mana-Chewore have shown only limited adoption of systematic data-based adaptive management. The drivers of adoption closely parallel the drivers of manager ownership and buy-in to adaptive management that I identified from interview data (Fig. 6.5).

| **Four drivers of adoption** | **Relevance to adaptive management in Mana-Chewore** |
|---|---|
| Performance expectancy | Park managers see traditional management styles (based on experience, intuition and only basic data use) as familiar and reliable. They generally do not see how data-based adaptive management will improve their anti-poaching efforts, partly because they do not fully appreciate its potential. |
| Effort expectancy | Managers are not comfortable with the specialist skills required for data analysis, which they perceive as unnecessarily complex time consuming compared to more basic data use (such as a map on the wall with pins indicating poached elephant carcass locations). |
| Social influence | Managers feel a strong obligation to record and report poaching data, due to external pressure from 'important others' – in this case, both the MIKE programme and their own organisation (Zim Parks). While mangers experience some social pressure to actually use these data adaptively, this pressure is weaker and there is little clarity as to what this actually means. |
| Facilitating conditions | The organisational culture at Zim Parks emphasises data collection and reporting over data use. The organisational structure takes responsibility for data analysis away from managers and places it with the science/ecology arm of the organisation. Also, basic facilitating infrastructure such as computers and digital displays are absent from many ranger stations in Mana-Chewore. |

*Is adaptive management appropriate in Mana-Chewore?*

The various factors that impede the successful implementation of adaptative management, both in the present study and in many others, rightly leads one to question the appropriateness of the approach in certain contexts. Are park managers in Mana-Chewore perhaps right to resist adaptive management? Based on an extensive analysis, Gregory et al. (2006) argue that in some contexts adaptive management may not be appropriate, such as when there is poor institutional and stakeholder support, or when the costs and benefits of implementing adaptive management are not clearly evaluated. In Mana-Chewore, while Zim Parks and MIKE ostensibly support adaptive management, the key end-users (park managers) do not. These managers are also very clear on what they see as the costs of implementing adaptive management, and do not appreciate or buy-in to the supposed advantages of the approach. Adaptive management is also compromised in contexts where managers do not have confidence in baseline monitoring data (Gregory et al., 2006). Although not a common objection, some respondents did question the consistency of elephant mortality recording and the reliability of inferred poaching trends, a suspicion that was borne out by the trend detection results presented in chapter 4. Based on a review of ranger-based monitoring for tiger conservation across eight sites in Asia, Stokes (2010) suggests that the biases in ranger-collected data (see chapters 3 and 4 of this Thesis) mean that such data may be more appropriate as a source of rapid information on illegal activities to which managers can tactically respond, rather than a source of data for longer-term trend analysis and adaptive management.

Gregory et al. (2006) conclude that the failed implementation of adaptive management may be less to do with the approach itself, but rather with its uncritical application. One of the problems identified in the analysis of interview responses was poor communication to park managers about what adaptive management actually is and, most importantly, what added advantage it offers over traditional management styles. Senior Zim Parks staff in particular described a “need for marketing” and “awareness campaigns” to foster a greater understanding among on-the-ground managers of the potential advantages of adaptive management. Notably, however, MIKE staff and senior Zim Parks staff spoke about adaptive management as an abstract concept, and less about specific ways that managers could use data adaptively. Managers saw systematic analysis of trends in poaching data as unfamiliar and unnecessary compared to traditional management practices based on intuition, experience, and more immediate reaction to shorter term poaching patterns. This raises the question of what exactly the advantages of adaptive management in Mana-Chewore might be. Table 3 presents specific examples and cases where data-based adaptive management could provide advantages over traditional management approaches. Importantly, there are legitimate uses of ranger-collected data that do not require systematic analysis or explicit evaluation of management strategies. Park managers in Mana-Chewore clearly valued and used ranger-collected data on elephant poaching to guide patrols deployments and provide a more qualitative sense of the level and nature of poaching threats. Thus, in the theory-of-change I develop below (Fig. 6.6), the goal is simply more optimal use of ranger-collected data as opposed to better implementation of adaptive management.

**Table 6.3.** Advantages of systematic analysis of poaching trends and adaptive management, over traditional management practices around elephant poaching. Specific examples of the potential application of adaptive management in Mana Chewore are also given. Advantages and examples are based on interview responses, personal observations, and the literature.

| **Advantages and examples** | **Details** |
|---|---|
| Advantage: a long-term data archive | Data-based management promotes consistent recording of data in a single historic database, which ensures long term data access (whereas intuition and experience is lost when a manager is transferred). |
| Advantage: escaping poor conclusions from biased data | Reacting to raw patrol data without appropriate analysis is susceptible to spatial and temporal bias due to non-random patrolling patterns (i.e., poaching hotspots may be misidentified; see chapter 3). |
| Example: identifying seasonal patterns in poaching | Plotting monthly counts of detected poached carcass can elucidate seasonal poaching patterns and appropriate responses. |
| Example: identifying longer-term annual changes in poaching | Analysing annual trends in poached carcass detections may help managers understand drivers of change, identify resource needs, and critically reflect on current management practices. |
| Example: explicitly evaluate management actions | Assessing how poaching levels respond to management actions can lead to the development of improved anti-poaching strategies (Fig. 6.1). |

Learning from new information, dealing with uncertainty in this information, and making decisions accordingly can be very challenging and requires the development of particular aptitudes (Tauritz, 2012). Expecting this from park managers without formal training, and without demonstrating the value of learning-by-doing, is perhaps unrealistic.

*Relieving managers of the full burden of responsibility for adaptive management*

A common expectation among managers was that the scientific arm of Zim Parks, and particularly the resident ecologist, should be responsible for analysing trends in poaching data and providing feedback. The demanding and diverse responsibilities of park managers, their common aversion to the technicalities of data analysis, and the specific training scientific staff have in this area, suggest that stronger collaboration between managers and the resident ecologist could foster more successful implementation of adaptive management. The various forms of data management and analysis required to unlock the advantages of adaptive management (Table 6.3), while difficult for managers in Mana-Chewore to carry out alone, may be much simpler for scientific staff of Zim Parks. Indeed, the monitoring and analysis elements of adaptive management in many other contexts are carried out by scientists, not managers (van Wilgen and Biggs, 2011). Interview data suggest that managers would be open to closer collaboration with scientific staff: *"They have the responsibility to analyse the data and give us advice. If they need the data, we can provide it"* (manager 9). Similarly, one of the senior scientific staff of Zim Parks said, *"We don't have to fight…we can do it together…let's look at this data together and make management decisions"* (national-level respondent 11). Despite these sentiments, close collaboration between scientific staff and managers around analysis of management-relevant trends in poaching data was evidently rare in Mana-Chewore.

The reasons for this were not investigated, but this result accords with the gap between research and management that is so common in environmental science, which amongst other things is attributed to poor engagement between researchers and managers and poor commitment of researchers to conservation implementation (Addison et al., 2015; Knight et al., 2008). This gap may be exacerbated by the organisational structure of Zim Parks, in which the scientific and management arms of the organisation remain separated and have different goals. In a similar case study of bushmeat hunting in the Serengeti, Tanzania, Nuno et al., (2014) interviewed respondents variously involved in research and management and found that the link between research and monitoring and management decisions was weak. Respondents ascribed this variously to poor communication of research results, research that was not management focussed, and low levels of trust in research which was seen as only an academic exercise. As a result, improving the implementation of practical conservation actions was seen as more important than further research and monitoring (Nuno et al., 2014). Looking ahead in Mana-Chewore, it will be important to better understand the barriers between scientific and management staff within Zim Parks in an effort to foster greater collaboration towards achieving adaptive management goals (Fig. 6.6). Given the lack of capacity and willingness of managers to conduct complex analyses themselves, there may also be a role for collaborations outside Zim Parks. The further development of the online dashboard (allowing easy access to summaries and plots of site-level poaching data) by the MIKE programme may be one example of this. There may also be a key place for independent researchers to collaborate with managers to develop the more complex models and methods needed to use ranger-collected data to reliably address key questions that are important to managers (as I attempt to do in Chapter 3 of this Thesis).

The MIKE programme originated from the need to inform CITES-level ivory policy and was not originally driven by the needs and interests of local park managers and national wildlife authorities (Blake & Hedges, 2004). MIKE staff respondents, while acknowledging this history and the broader CITES policy mandate, did however express a strong organisational impetus towards engaging more actively with park managers and local elephant management. Interview data suggest, however, that the perspectives, needs, aspirations and preferences of park managers have still not been adequately considered in the design and implementation of programmes like MIKE and SMART. These programmes aim to promote and facilitate adaptive management but are largely externally driven.

The field of human-centred-design (HCD) may provide a way forward – it seeks to develop products or services that are tailored to the behaviours, needs and current practices of the individual user (Steen, 2011). Although HCD is most commonly applied to innovations within computer and information technology, its principles help explain the limited adoption of data-based management in Mana-Chewore. My results suggest that data-based management does not fit well with the current behaviours and practices of park managers, neither does it address a need that they themselves have articulated. The HCD approach complements, and in certain respects improves upon, theories of adoption (like the UTAUT discussed above) by focussing on actual people rather than abstract 'users' (the latter can be subtly dehumanizing; Jordan, 2002). The approach seeks to ensure that users actually *want* to use the product and are *able* to use it (Steen, 2011).

Reflecting on the HCD approach with reference to my particular case study, it would appear that a significant problem with adaptive management as currently implemented in Mana-Chewore is that it fails to properly address the current decision-making practices of managers. How do managers currently make anti-poaching decisions in Mana-Chewore? What social, logistical, and personal factors most influence these decisions? What information do managers currently used to develop anti-poaching strategies? A key result was that the currently promoted forms of adaptive management make oversimplifying and abstract assumptions about the way managers make decisions. Similarly, based on three case studies of adaptive management in Canada, McLain and Lee (1996) argue that a major flaw was poor assumptions about how environmental decisions are made and implemented. Nuno et al. (2014) rightly argue that managers do not make decisions in a vacuum but are shaped by a variety of socio-economic and political factors. In his research into Environmental Impact Assessment decisions in South Africa, Lloyd (2018) found that, while scientific evidence was highly regarded in the process, social factors like informal negotiations between key stakeholders had an important influence on decision-making. The point here is that monitoring data are typically only one of many factors affecting decision-making. Unfortunately, my research did not explicitly seek to understand the decision-making processes of park managers in Mana-Chewore. Such research is crucial to the development of solutions that seek to optimize the use of ranger-collected data in the decision-making processes of managers (Fig. 6.6). This would help place the role of systematic data analysis in decision-making within a broader context of other factors that shape decisions, thereby laying the ground for the (human-centred) design of more realistic ways for ranger-collected data to inform decisions.

Another way to achieve human-centred design is the active involvement of users in the development of the innovation, so that their experiences and concerns are understood at the outset (Kujala, 2003). Park managers, once they begin to see tangible examples of how data-based management might be beneficial in some cases (Table 6.3), will have ideas and practical knowledge about how the approach might best fit within their context. If managers are engaged to provide their own ideas for how ranger-collected data might be used in their decision-making processes and given the opportunity to say what they would find most useful from an adaptive management programme, they might be more prepared to take ownership of it (Fig. 6.6). It is important, however, that a range of potential users are involved and that the designer/innovator (in this case the MIKE programme or senior Zim Parks staff) is still given room to articulate the proposed innovation (Steen, 2011). This is because users may vary widely in their practices or preferences and may not always be able to articulate their needs or grasp the purpose of the innovation.

*A theory-of-change for maximising the potential of ranger-collected data to contribute to enhanced anti-poaching decisions in Mana-Chewore*

Fortunately, the beliefs that individuals hold about an innovation are often malleable (Straub, 2009). Greater adoption is possible by carefully addressing the cognitive concerns of users, such as the performance gains that they expect from the innovation, or the ease of its use (Table 6.2; Venkatesh et al., 2003). Below I propose a theory of change for achieving the goal of park managers making optimal use of ranger-collected data to inform their anti-poaching decisions. using my interview findings together with key concepts from adoption theory and human-centred design (Fig. 6.6). Importantly, the overall goal is not greater adoption of adaptive management in Mana-Chewore *per se* (my analysis shows that such a goal is too abstract), but rather the aim is to achieve enhanced anti-poaching efforts through more effective use of ranger-collected data. Achieving this goal will involve both (a) continuing with current forms of data use, and (b) identifying opportunities for innovation (which will inevitably involve some elements of systematic adaptive management).

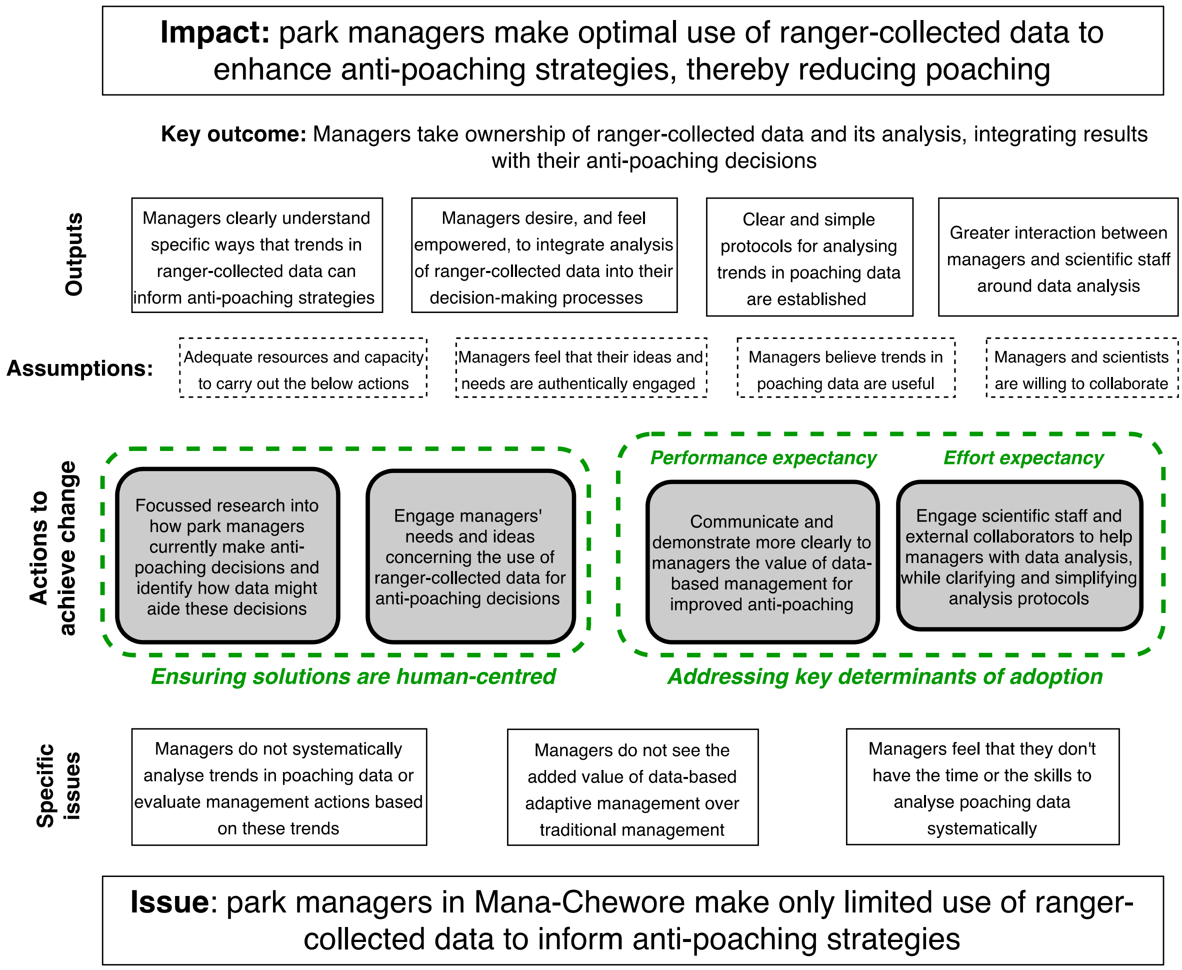



**Figure 6.6**. A theory of change outlining pathways and actions for achieving the goal of enhanced anti-poaching outcomes through greater use of ranger-collected data by park managers in Mana-Chewore. This theory has been developed based interview findings, as well as key concepts from technology adoption theory (Venkatesh et al., 2003) and human-centred design (Steen, 2011).

*Conclusion*

This chapter investigated how park managers in Mana-Chewore currently use ranger-collected data on elephant poaching. I found that park managers valued such data and used them to guide patrols. Managers did not, however, systematically analyse trends in ranger-collected poaching data, nor did they adjust their anti-poaching strategies in response to these trends. A major reason for this is that managers perceived because the costs of adopting such an adaptive management approach to outweigh the benefits. Specifically, managers were unfamiliar with the technicalities of data analysis and felt that management based on intuition, experience and more reactive data-use was both more familiar and more dependable. As a result, there is a low level of ownership of data-based adaptive management among managers. Furthermore, the perspectives, priorities, and needs of park managers have not been adequately considered in the MIKE and SMART programmes that are seeking to promote adaptive management in Mana-Chewore. Looking ahead, it is necessary to demonstrate more clearly to managers the potential benefits of systematically analysing poaching trends, and to minimise the perceived effort and cost of adaptive management (by sharing responsibility for data management and analysis with others, for example). There is also a need to better understand the decision-making context of managers, and to work directly with mangers to identify specific ways in which ranger-collected data could inform key management decisions.

# Chapter 7: Synthesis and Discussion

In this Chapter I will discuss the contributions of this DPhil research to the field of conservation science and highlight the ways in which my findings have advanced socio-ecological systems research. In each of the five sections below, I identify a key higher-level insight, or theme, that cuts across two or more of the data Chapters in this Thesis. In each section I will review previous work around the theme, summarise the insights and contributions of my research in the area, and look ahead to priorities for future conservation science and practice. I conclude by briefly re-visiting my overall study objectives and considering how my four data Chapters have addressed these.

## 7.1. The power of interdisciplinarity in conservation science

Interdisciplinarity is a concept that has grown rapidly within academic and popular discourse (Fig. 7.1). Interdisciplinary methods to understand the human and nature elements of socio-ecological systems are often discussed but less commonly carried out (Pooley et al., 2014). Researchers have long recognized the importance of the social sciences for understanding environmental challenges (Adams and others, 1996; Scoones, 1995). After all, conservation is, to use the oft-cited adage, about people. We can get the ecology and mathematics right, and still find that conservation interventions fail in the real world of people, power and politics (Mascia et al., 2003). Understanding people's behavior in the context of their engagement with nature is essential to designing effective conservation strategies (St John et al., 2013). In her high-level conceptual review, Milner-Gulland (2012) stresses how important interdisciplinary approaches are for understanding the complex interactions between conservation interventions, human behavior, and biodiversity loss. Although it has been advocated for decades, interdisciplinary research in environmental science is still nascent (Hicks et al., 2010).

I hope that the novel insights I was able to gain through an interdisciplinary approach (detailed below) will help advocate such an approach in conservation science going forwards.

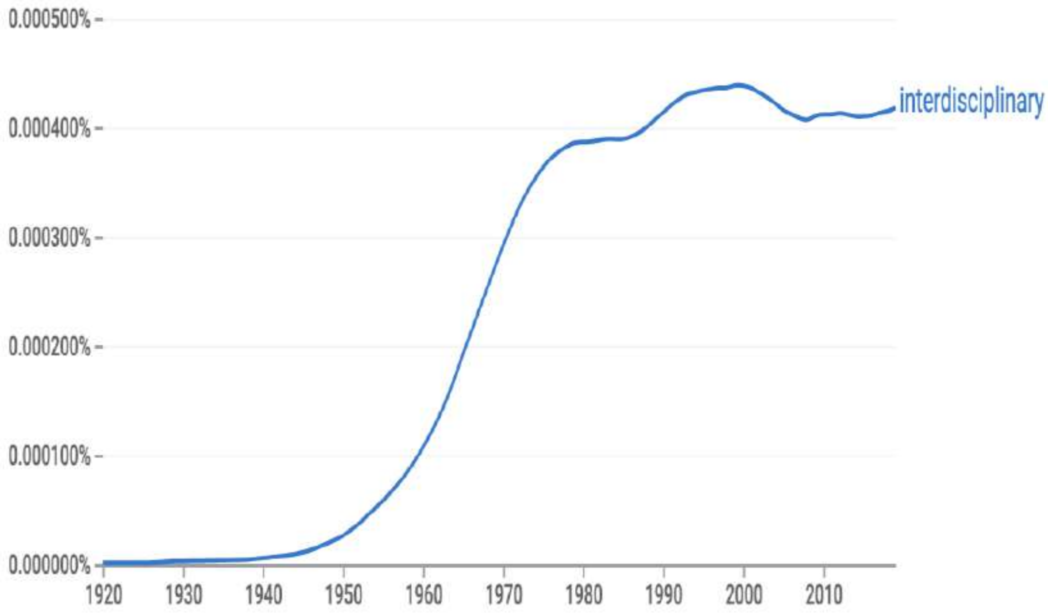



**Figure 7.1.** A Google “Ngram” showing the change in frequency of usage of the word “interdisciplinary’ based on mentions within books in the Google Books archive (Accessed 4 December 2020).

Before describing the interdisciplinary approaches I took in my research, I want to briefly review three case studies that exemplify the novel insights and real-world impact attainable through integrating the natural and social sciences. These are based on work by my colleagues at the Interdisciplinary Centre For Conservation Science. Brittain (2019) used mixed methods to gain a deep understanding of how local ecological knowledge could be incorporated into robust wildlife population monitoring, using a forest case study in Cameroon. In an exemplary analysis, she used qualitative data in the form of interviews with local villagers and the diaries of local hunters to feed into quantitative occupancy models, in order to better understand the distribution and abundance of various forest species (also comparing findings to those from more traditional camera trap surveys). Doughty (2020) combined insights and methods from behavioral science disciplines (e.g., public health) with insights from wildlife trade research to design, implement, and evaluate an intervention targeting the behavior of consumers of traditional Chinese medicine products that use the horn of the endangered saiga antelope. Arlidge (2020) used mixed methods to critically evaluate and expand on theory and approaches for mitigating the biodiversity impact of human activities and development, with a focused case study of sea turtle bycatch in Peru fisheries. He used a diversity of methods, including expert elicitation to estimate bycatch rates, and social network models to estimate the potential of information spread about bycatch reduction interventions among fishers.

*Insights from interdisciplinary approaches in this DPhil research*

The aspect of this DPhil research that I found simultaneously most challenging and rewarding was its interdisciplinarity. My academic background prior to this DPhil was largely natural science focussed and strongly quantitative, so it was a challenge for me to engage with new qualitative methods. I have discovered, however, that truly interdisciplinary science involves more than combining methods from diverse fields, but also engaging with and harnessing the power of different epistemologies, that is, different ways of looking at and gaining knowledge about the world. Along with the qualitative methods I learnt through collecting interview data for my research, I also had to engage with broader theories within the social sciences, such as occupational culture and theories of technology adoption. In the process, I have discovered that quantitative and qualitative methods can provide mutually enriching data on the same study system. I often found that it was only when I considered the numbers (such as the power of ranger-collected data to detect trends in poaching) alongside the narrative (such as the ways in which park managers actually use ranger-collected data), that I was able to really gain a broader understanding of my study system and to begin having something meaningful to say about my research questions.

Perhaps the part of my research where I saw the power of interdisciplinarity most clearly was in Chapter 3, where I explicitly sought to engage the insights and perspectives of park managers and rangers in order to help me build and later evaluate statistical models of spatial patterns in elephant poaching. For this I had to engage with the concept and philosophy of participatory research approaches, which recognize the analytical agency and knowledge of often disempowered groups (Chambers, 1994). I engaged the perspectives of park managers and rangers at two levels. Firstly, they helped me understand the factors driving the behaviour and movements of poachers, elephants, and rangers so that I could select candidate variables for predicting spatial patterns of poaching using species distribution models. Secondly, participants helped me not only to interpret and understand the results of my statistical models but also to interrogate their reliability. This led me to question the assumptions I had made during the modelling process. I actually started with a more 'external' perspective in which I thought I was returning to the field primarily to tell rangers and managers about my findings and the potential biases in their data, but I ended up learning from them (Danielsen et al., 2009). By combining interviews, focus groups, and statistical models, I was able to distinguish underlying spatial patterns in elephant poaching from those explained by patrol bias.

Chapter 4 provides another example. The strength of the virtual ranger mathematical simulations developed in this Chapter depends on the reliability with which they represent the poaching and patrolling dynamics at my Mana-Chewore field site. Furthermore, the value of the simulation results for conservation management depends on how well they address park manager needs regarding measuring patterns in underlying poaching. The understanding I gained through interviews and personal observations during two field visits to ranger stations in Mana-Chewore helped me to parameterise my model based on a good understanding of site-level elephant poaching (Chapter 3) and ranger-based monitoring (Chapter 5), and to design the model to answer questions that I understood to be important to park managers at the site. This involved both direct questions about certain features and parameters of the system and gaining a more indirect and holistic 'feel' for the way things work at Mana-Chewore through my own observations and informal conversations.

Ultimately, however, the greatest advantage of the interdisciplinary approach I have taken here is not in the insights gained within any one Chapter, or in how I used information from a qualitative Chapter to inform a quantitative one, but rather in the higher-level insights I was able to gain by looking at results across Chapters. This synthesis Chapter highlights some of these insights and how they ultimately constitute what I see as the main contribution of my work. Chapters 4 and 6, for example, used vastly different methods, but the results of both point towards the importance of clearly defining goals for monitoring. This is discussed further in section 7.4 below. Similarly, when considering Chapters 4 and 5 together, it is clear that the effectiveness and sustainability of ranger-based monitoring must involve steps towards improving reliability (e.g., through increasing patrol effort) and towards more meaningfully engaging the rangers themselves (e.g., through providing feedback to them on how the data they collect are used). As another example, Chapter 5 revealed that one of the most common ways that park managers in Mana-Chewore use ranger-collected data on elephant poaching is to identify hotspots of poaching in space, while Chapters 3 and 4 revealed that poaching in Chewore is fairly spread out across space, and that spatial patterns of poaching may change through time. These results together help elucidate how this particular use of ranger-collected data (which is common; Critchlow et al., 2015; Moore et al., 2018) may best be leveraged for conservation management.

*Fostering future interdisciplinarity*

From its genesis in the natural sciences as '*Conservation Biology'* (Soule, 1985), the science of conserving biodiversity has evolved to embrace methods, theories, and epistemologies from a variety of disciplines (as the case studies reviewed above illustrate). This has been a welcome change, and while it started decades ago, there are yet new frontiers to explore. It is encouraging that there are growing efforts both to mainstream the social sciences in this field (Bennett et al., 2017), and to train and equip a more interdisciplinary generation of 'socio-ecological' researchers (Kelly et al., 2019). Indeed, it has been a great privilege to carry out this DPhil work within a research group that is at the forefront of this movement, and under the supervision of a mentor who is a prominent champion of it. There are still, however, barriers to interdisciplinarity, such as vastly different disciplinary 'languages', departmental silos, and time and resource constraints, that need to be overcome (Kelly et al., 2019). Another barrier is that academia as a whole, and the rewards and incentives within it, is still largely organised along disciplinary lines (Hicks et al., 2010). There is also a tension between being a specialist within a team of other different specialists, and becoming interdisciplinary oneself (Pooley et al., 2014).

These barriers make it difficult to develop as an interdisciplinary scientist. One solution, suggested by a group of early-career interdisciplinary scientists, is to create specially organised 'encounters' that foster open communication between researchers in different fields (Bridle et al., 2013). Kelly et al. (2019) helpfully provide a list of ten practical tips for developing as an interdisciplinary scientist, targeted at both early career researchers and their mentors. The tip that resonated most with me was "develop an area of expertise". I think that such an approach helps one to keep an 'anchor' from which to launch one's interdisciplinary endeavours, and also helps to bring valuable expertise to the interdisciplinary table. Finally, based on my experience in this DPhil, perhaps what is most needed is for more early career researchers to be actively exposed to or be challenged to employ interdisciplinary approaches, as opposed to only talking about them.

## 7.2. Embracing uncertainty in conservation science

My case study involved the monitoring and management of elephant poaching in Zimbabwe – a complex and uncertain socio-ecological system. My results show both how prevalent the effects of uncertainty can be, and how accounting for these uncertainties can lead to better (more realistic and robust) conservation action. A major insight from this research, therefore, is the importance of embracing uncertainty (Milner-Gulland and Shea, 2017). As outlined in Chapter 1, I focus specifically on two classes of uncertainty; observation uncertainty and implementation uncertainty.

*Understanding and addressing observation uncertainty*

Chapters 3 and 4 focus on observation uncertainty - the discrepancy between the true state of a socio-ecological system and what is actually observed through monitoring. In my case study, the poached elephant carcasses that rangers observe are only a partial representation of underlying patterns of poaching. Chapter 3 focusses specifically on reducing observation uncertainty by accounting for spatial bias in ranger patrols in order to generate more robust estimates of spatial patterns in poaching. Chapter 4 provides a much broader analysis of the diverse factors that mediate how closely ranger-collected data captures underlying trends in poaching. These include many observational factors to do with the patterns of patrols and carcass detectability (the observation process), but also how these observation uncertainties interact with structural uncertainties to do with the behaviour of the study system itself (Fackler and Pacifici, 2014), such as true poaching levels and trends.

Ranger patrols do not cover all areas equally, which leads to obvious uncertainty concerning whether observations collected during patrol reflect underlying patterns or simply the pattern of patrolling (Critchlow et al., 2015). In Chapter 3, basic patterns in quantitative data on ranger-detections of elephant carcasses in Chewore revealed large areas where there were no records of either poaching or natural mortalities. This, together with interviews with rangers and managers, revealed that the more mountainous areas of Chewore are seldom patrolled because of challenging terrain and because elephants themselves do not frequent these areas. Rangers also judged that poachers avoid these same areas for similar reasons. It was uncertain, however, whether there was in fact less poaching in these areas, or whether poaching there simply went undetected. It is this kind of uncertainty that is often ignored by both researchers and managers – such as in a similar analysis of elephant poaching patterns in a nearby protected area in which potential bias in the ranger patrols used to collect these data was not accounted for (Sibanda et al., 2015). To help address this uncertainty within the ensemble species distribution models that I used to spatial poaching patterns, I used several different sets of background data to match the spatial bias in ranger patrols. Each set had slightly different assumptions about patrol bias and produced different predictions, and it was the evaluation of these predictions by rangers and managers that helped me to arrive at robust inference. A key insight from this Chapter, therefore, is the power of combining different qualitative and quantitative methods in order to reduce uncertainty in our understanding of socio-ecological systems.

The virtual ranger model in Chapter 4 sought to explicitly quantify uncertainty in the ranger-based monitoring observation process by quantifying likely levels of bias and imprecision in ranger-collected data under realistic scenarios of poaching and patrolling. Perhaps the most important insight here was that detecting spatial and temporal patterns in poaching through ranger patrols can be very difficult, particularly for temporal patterns. Only large temporal trends in poaching (a 75% change from baseline levels) were detectable with reasonable power at low patrol effort levels, whereas moderate (50%) changes in poaching required high levels of effort to detect, and smaller (25%) changes in poaching were almost impossible to detect. Results varied according to both underlying poaching dynamics (e.g., whether poaching was increasing or decreasing), and patrol strategy (e.g., whether patrols were spatially constrained or not). Chapter 4 also showed that different assumptions about underlying poaching dynamics, such as space-time dependence in poaching and the level of clustering of poaching hotspots, influenced the power of ranger patrols to detect these dynamics. Indeed, the effects of space-time variation were not as large as might be expected, because carcasses were actually quite spread out in Chewore (based on the empirical models of Chapter 3). Thus, process uncertainty in our understanding of actual system dynamics can interact with observation uncertainty to confound patterns in ranger-collected data.

A key conclusion from these results is that uncertainty in trend detection is very large, and it is crucial that this uncertainty is acknowledged by both park managers and those designing ranger-based monitoring programmes. A high degree of uncertainty in trend detection has been similarly demonstrated in many other monitoring contexts, such as ecological surveys of illegal hunting in Sierra Leone (Jones et al., 2017), aerial surveys of ungulates in the Serengeti (Nuno et al., 2015), and ranger detections of bushmeat snares (Ibbett et al., 2020). Global monitoring indicators, such as the Living Planet Index, which tracks trends in numerous species populations, may also yield data trends that are highly uncertain (Jaspers, 2020). Interviews and informal discussions with rangers, managers, and senior staff of the Zimbabwean wildlife authority (Chapters 5 and 6), suggested that patterns in ranger-collected data were often taken at face value, without acknowledging the inherent uncertainty in these data. The expectations that stakeholders have about the reliability of inferences from monitoring data may often be unrealistic. Explicitly acknowledging uncertainty, and seeking to quantify it, can help put results from ranger-based monitoring into their proper context, and highlight ways in which to reduce uncertainty (which may involve trade-offs with the other important goals of ranger patrols such as law enforcement; Stokes 2012). Explorations of drivers of uncertainty, such as the virtual ranger simulations of Chapter 4, can also help park managers to design monitoring and management strategies that are both effective and robust to uncertainty (Nuno et al., 2017). In section 7.3 below I discuss how models are an effective means for both understanding and accounting for the observation uncertainties discussed in this section.

*Qualitative investigation to understand and address implementation uncertainty*

Another category of uncertainty that I found to be important to the reliability of ranger-collected data and its effective contribution to evidence-based conservation, is implementation uncertainty; that is, the discrepancy between the expected and the actual outcomes of conservation interventions. Chapters 5 and 6 focus on the behaviour, the work environment, and the broader social and institutional context of rangers and park managers - the two stakeholder groups central to the successful implementation of an effective ranger-based monitoring and management system.

Research on implementation uncertainty in natural resource management has mostly focussed on the people whose behaviour a conservation intervention seeks to change, acknowledging that factors like non-compliance with conservation rules may lead to uncertain intervention outcomes (Bunnefeld et al., 2011; Nuno et al., 2014). For example, the generic natural resource management model developed by Milner-Gulland (2011) incorporated decision-making by resource harvesters and showed that poor management outcomes result when harvesters are not monitored to ensure they comply with harvesting rules. Similarly, Keane et al. (2012) modelled how individual resource users would respond to penalties for breaking resource harvest rules, and to payments for monitoring other resource users to ensure compliance with rules. They found that payments and sanctions interact strongly with each other in ways that vary according to the socio-economic context of resource users. These examples underscore the importance of planning for, and as far as possible addressing, the varied and uncertain ways that resource users will change their behaviour in response to conservation interventions. This is because human behaviour often has a strong influence on the outcome of conservation management (Fulton et al., 2011). In my Thesis I frame implementation uncertainty in a slightly different way by shifting the focus from resource users to those actually responsible for managing and monitoring these resources. I show that uncertainty in the behaviour, motivations and priorities of rangers and park managers means that the outcomes of the conservation interventions that depend on them as key agents are themselves uncertain. In both Chapters 5 and 6, I show how better understanding the perspectives of, and pressures on, rangers and managers can help overcome the unexpected outcomes that might arise when these perspectives are ignored (such as managers not using monitoring data to inform their decisions).

Chapter 6 provides perhaps the clearest example of the implementation uncertainty (and even failure) that can arise when conservation programmes are insensitive to the context and needs of the people who are supposed to implement them. In my case study, adaptive management - whereby monitoring data are analysed to evaluate and improve management actions – has been promoted as a management approach by both the national wildlife authority in Zimbabwe and an international programme for monitoring elephant poaching (MIKE). Yet my results showed only very limited adoption of data-based adaptive management in Mana-Chewore. This was mainly due to very low levels of ownership among key stakeholders – the park managers themselves. These results echo those of Addison et al., (2015), who found that managers across variety of Marine Protected Areas in Australia made only limited quantitative use of data from long-term ecological monitoring programmes, preferring instead to use only a qualitative consideration of broad trends in data and their own management intuition. Similarly, Sutherland et al., (2004) found that biodiversity managers in the United Kingdom tend to prefer common sense, experience, and discussions with other managers over primary scientific evidence to guide their decisions.

Interviews with managers in Mana-Chewore revealed that they saw systematic analysis of trends in ranger-collected data on elephant poaching as both less reliable and less familiar than traditional management approaches based on intuition, experience and more reactive use of data. Many managers felt uncomfortable with the technical aspects of data analysis. They also felt that adaptive management as currently promoted in Mana-Chewore was too ‘slow’ an approach when there was an immediate poaching crisis to respond to. From a programme design perspective, the purpose of adaptive management and tangible examples of its advantages were not well communicated to managers. Furthermore, both the MIKE programme and the institutional structure of the government wildlife authority was strongly geared towards data recording and reporting but did not emphasise the use of these data for local anti-poaching decisions. These problems may be summarised by concluding that uncertainty in the behaviour of park managers was not accounted for, because their perspectives were not properly engaged.

Chapter 5 provides a further example of this implementation uncertainty. Interview results show that the way rangers perceive patrol-based data collection, specifically how they see it fitting with their broader responsibilities and whether or not they are aware of how their data are used, affects their meaningful engagement with monitoring. Also, the occupational culture of rangers and their living environment was shown to shape their motivation and work ethic. Although I did not directly measure the effects of these factors on the quality of data collection, interview data suggested that they strongly affect the consistency and sustainability of ranger-based monitoring. The occupational culture of rangers at my study site (particularly the strong sense of duty and deference to authority that they demonstrated) had a strong influence on how rangers engaged with monitoring. Rangers saw data collection as a fundamental duty and reporting data as an opportunity to demonstrate a job well done to their supervisors. I discussed how more engaged data collection can be achieved by building on existing ranger culture while also fostering rangers' appreciation of data collection and utilization thereof. These results accord with the seminal work of William Moreto and colleagues, which emphasizes the importance of investigating ranger perspectives and ideas as being key to the success of conservation interventions, rather than seeing them as passive nodes through which these interventions are enacted (Moreto et al., 2017; Moreto and Lemieux, 2015). Again, as in the case of implementing adaptive management, the behaviours, preferences and perceptions of the rangers tasked with actually carrying out ranger-based monitoring are tantamount. Without properly considering these human dynamics, the outcomes of ranger-based monitoring and management would be far from certain.

*Embracing uncertainty in future socio-ecological systems research.*

Looking ahead, the most straightforward recommendation arising from my research is that those researching socio-ecological systems should seek to identify key uncertainties in their system and explicitly incorporate them into their research questions. As discussed above, models provide a useful tool for achieving this. Future research might also focus on the development of novel statistical techniques for accounting for observation uncertainty, which itself depends on research that seeks to understand and measure the processes that bias the observation process (Dobson et al., 2020). Another contribution for researchers to make is not only to quantify specific forms of uncertainty, but to investigate what they mean for management decisions. For example, if ranger patrols are only able to reliably detect very large changes in poaching over time, how then should managers use ranger-collected data? How should managers make decisions under this kind of uncertainty? Earle (2016) provides an example of such a recommendation, suggesting that managers might better base their decisions on the presence/absence of threats based on community monitoring, rather than trends in these threats (which she showed were very uncertain). Another key area for future work is to make the link between monitoring data and management decisions more explicit and practicable. An excellent example of this is the concept of decision triggers, where management actions are explicitly designed to respond when monitoring data indicate that a key ecological variable (such as the abundance of individuals of a certain species) drop below a particular threshold level (Cook et al., 2016).

## 7.3. The value of models for understanding and addressing uncertainty in socio-ecological systems

The results of Chapter 3 and 4 point more generally to the value of models - which I understand here as representations of reality created for a particular purpose. Models provide an excellent means of incorporating our uncertainty about the underlying reality that they seek to represent and exploring its implications (Regan et al., 2002). Models are thus an essential way to embrace uncertainty, as advocated in section 7.2 above. They also help researchers explore, and thus comprehend, their study system in ways not possible through direct observation.

The virtual ranger model I developed in Chapter 4 is an example of this: it sought to represent the elephant poaching and ranger patrol dynamics at my study site through simulation, thus allowing for virtual exploration of processes and mechanisms that are likely to be occurring in reality but which are not observable. The obvious advantage of this modelling approach is that it overcomes the challenge of not having independent data on true poaching levels. Instead, I simulated realistic patterns of underlying poaching directly, based on parameterisation using the best empirical data available. The model thus helped me determine how accurately and precisely ranger-collected data represent underlying poaching levels under realistic scenarios, which is crucial to assessing ranger-based monitoring as a conservation tool. Similarly, although ranger patrol bias was not observed directly, the statistical models of Chapter 3 involved testing assumptions about ranger patrol bias (in particular where to sample background data from) and were thus able to produce more robust inference. More broadly, by representing our best current understanding of a particular system under study, models provide a tool for thinking critically about system dynamics and the specific questions one hopes to answer about these dynamics (Addison et al., 2013). Thought of in this way, models need only be as complex as the particular research questions demand. In the context of fisheries management, Plagányi et al. (2014) show that ecosystem models of intermediate complexity, which focus on one particular aspect of a broader ecosystem over shorter time scales, can be an effective way of addressing focussed management questions.

To make this discussion of the advantage of models less abstract, I will use another illustrative example from the literature. Bunnefeld et al. (2013) developed a management strategy evaluation model to help guide trophy hunting of the endangered Nyala antelope in Ethiopia. The population dynamics of nyala (including both hunting and poaching offtake), population monitoring, and the decision-making of both the government and the private hunting operator, were all incorporated within the model. The government and hunting operator could choose between investment in anti-poaching and better population monitoring, and management performance was measured both by profits from hunting offtake and population viability. Results showed that poaching had a larger effect on sustainable offtake levels than did uncertainty in population estimates, suggesting that anti-poaching investment was crucial. A certain level of consistent monitoring was however required for appropriate planning and quota setting. This model helped make explicit the assumptions about the effect of key processes like hunting offtake, poaching intensity, and uncertainty in population estimates. It also allowed exploration of the outcomes of various possible management actions without having to engage in expensive and risky real-world experimentation.

In a comprehensive treatment of the use of models in applied conservation science, Milner-Gulland and Rowcliffe (2007) suggest that a key advantage of models is that they make assumptions as to how a system works explicit, thereby providing transparency for decision-making. Models also allow for the prediction of outcomes of certain management approaches that would be difficult to predict from intuition or a qualitative understanding of system dynamics alone. For example, it would be very difficult to predict how the effect of ranger patrols in deterring poacher activity might interact with changes in poaching due to exogeneous factors (like changes in the price of harvested species outside) to influence the reliability of catch-per-unit effort indices of poaching (as the models in Dobson et al. (2019) were able to achieve). Similarly, the virtual ranger model in Chapter 4 produced several non-intuitive results, such as the similarity in performance of random and spatially-targeted ranger patrols for detecting both spatial and temporal patterns in poaching, and also the notable differences in the difficulty of detecting increasing versus decreasing temporal trends in poaching.

In the context of this discussion, however, the greatest advantage of models is that they provide a means of directly incorporating inherent uncertainty in both our current understanding of a particular study system, and the way in which this system might respond to management action. This was a key feature of the mountain nyala hunting model outlined above, in which uncertainty in both monitoring and population dynamics was directly incorporated in order to help ensure that management recommendations were not only effective in terms of particular performance measures, but were also robust to uncertainty (Bunnefeld et al., 2013). Regan et al. (2005) used information-gap theory models to evaluate management actions for the Sumatran rhinoceros *Dicerorhinus sumatrensis*, showing that there was a sharp trade-off between management strategies that maximised conservation outcomes and those that were most robust to uncertainty. This is similarly well illustrated in the generic natural resource harvest and management model developed by Milner-Gulland (2011), which incorporated both uncertainty in estimates of the resource population from a monitoring programme, and uncertainty in how resource users might respond to management regulations designed to ensure harvest sustainability (i.e., they may not comply). In my study system of Mana-Chewore, both the absolute level of poaching and the baseline detection probability of poached carcasses by rangers is uncertain, and in Chapter 4 I was able to model different levels of these key variables in order to better understand the implications of this uncertainty. Similarly, I was able to quantify uncertainty in the power of ranger-patrols to detect simulated patterns in poaching, thereby allowing for an appraisal of ranger-based monitoring that was more realistic in that it was sensitive to uncertainty.

Participatory modelling (which I used in Chapter 3) is a particularly useful approach to addressing uncertainty Defining this approach is difficult as it comes in many forms. Essentially, it involves explicitly engaging stakeholders (those people connected to the system being modelled) in the process of modelling system dynamics, where the model is designed to inform a decision-making process involving these stakeholders (Basco-Carrera et al., 2017). Stakeholders may variously help define the goals of the model, identify important processes and relationships to be included, help define the form of these relationships, or help evaluate and interpret model outcomes. In my case study, rangers and park managers helped me to build and evaluate models of the spatial distribution of elephant poaching. Specifically, they helped with (1) selecting predictor variables based on their knowledge of ranger, poacher and elephant behaviour, (2) understanding and mapping the pattern of ranger patrols in space, and (3) critically evaluating model outcomes and assumptions. This third contribution was particularly valuable, as rangers and managers questioned the validity of the outcomes of one particular model scenario, which led me to realise that it was based on poor assumptions. As a result, I identified an alternative scenario as more robust, and it was from this scenario that I was able to draw final conclusions about spatial patterns in poaching.

Essentially, participatory modelling helped me to reduce uncertainty in my knowledge of the system by engaging the perspectives of those with more intimate knowledge. In their review of participatory modelling in fisheries management, Röckmann et al. (2012) similarly relate how a major advantage of the approach is that it reduces the uncertainties so prevalent in our scientific understanding of resource and harvest systems. Through an applied case study, these authors demonstrate shared learning, structured discussion between scientists and stakeholders and scientists around uncertainty, and increased legitimacy and trust in model outcomes as further advantages of the approach (Röckmann et al., 2012). Voinov and Bousquet (2010) further show how such an approach can increase stakeholder knowledge of the natural resource system and its use, while also clarifying the possible impacts of candidate solutions to management problems. Finally, I found that rangers and managers were more likely to engage with and take ownership of the results of the spatial model of elephant poaching, knowing that they were involved in the process. In their review of bio-economic models for marine fisheries management, Nielsen et al. (2018) also suggest that modellers spend more time discussing model outputs with the fishers.

I will end this discussion on the advantages of models by considering a crucial element of model-building – ensuring that models represent reality well. A quote from Albert Einstein is apposite here: "*one should make models as simple as possible, but not simpler*". Striking the balance between model complexity and simplicity is difficult and will depend both on the quality of the data available for model parameterisation (hence reducing the need for too many assumptions in more complex models), current qualitative knowledge of system dynamics and, crucially, the specific questions one hopes to answer using the model (Getz et al., 2017). The philosophy of Occam's razor suggests that simpler explanations (models) are more likely to be correct, and that the more assumptions you have to make (such as when building a model), the less likely the explanation. Following this principle, I sought to build the virtual ranger models in Chapter 4 with just enough complexity to answer my research questions. This meant, to use one example, deciding not to model age- and sex-structured elephant population and poaching dynamics, because the effects of poaching on elephant populations were unrelated to my research questions.

Einstein, however, warns against making models too simple. Occam himself held that if a complex explanation (model) does a *better* job than a simpler one, then the more complex explanation should be preferred. Furthermore, one of the major criticisms of models from conservation practitioners is that they unhelpfully simplify or abstract complex reality and do not properly capture processes that key stakeholders feel are important (Addison et al., 2013). Thus, I endeavoured to incorporate complexity where data allowed. For example, I included the relatively complex process of space-time dependence in underlying poaching into my virtual ranger models, because I hypothesised that this could have large effects on the reliability of ranger-collected data (especially in the case of targeted patrols which were guided by previous detections). Ultimately, however, the strength and usefulness of the models developed in this Thesis (both in Chapters 3 and 4) are vulnerable to the quality of the quantitative and qualitative data I used to parameterise them. Whilst I invested heavily in qualitative data collection and was given access to a comprehensive long-term data base of elephant mortality, I did not have raw data on one significant element of this system – fine-grained data on the pattern of individual ranger patrols. I thus had to make assumptions about the pattern and intensity of ranger patrols on the basis of qualitative data, and then model these patterns quantitatively. I also had to make assumptions about the baseline detectability of elephant carcasses (the probability that a carcass would be detected in a given grid cell of the park if that cell was patrolled), a parameter that would have large implications for patrol performance. This, however, points back to a significant advantage of models – they allow one to make these sorts of assumptions explicit, and to test the effect of alternative assumptions.

Looking ahead, it is likely that techniques for building and implementing models of socio-ecological systems will become increasingly sophisticated as the interface between mathematics, ecology, and statistics is strengthened. At the same time, data are likely to become both more available and of higher quality as monitoring technologies and remote sensing continue to develop. This will be a double-edged sword, as models become both easier to implement and therefore easier to thoughtlessly apply. My results have shown that balancing model complexity and simplicity, and being clear about the questions you hope to ask from a model, are crucial (Plagányi et al., 2014). It is in these areas that modellers can go wrong, even with the most sophisticated methods and high-quality data. There is thus a need for individual researchers, as well as teachers and supervisors, to develop the 'art' of modelling alongside the 'science' of modelling. There is a need for guidance on how to strike the balance between model complexity and adequacy (as in Getz et al., 2017), when it is suitable to make assumptions, and how to gear models towards focussed research questions. Another fruitful avenue for the future development of models in socio-ecological systems research, and one that is already growing, is the careful inclusion of expert judgements and knowledge in cases where empirical data are lacking (Martin et al., 2012). Finally, as discussed above, I think there are great gains to be realised through participation of a broader array of stakeholders in the modelling process, both to help build models and to evaluate and interpret their outcomes and potential application.

## 7.4. Begin with the end in mind: clearer goals for conservation monitoring

*Making the link between monitoring results and management decisions explicit*

Considering both my findings in this Thesis and the wider literature, a significant barrier to the effective contribution of baseline monitoring to improved biodiversity outcomes is that the purposes for which monitoring data are collected are seldom articulated well (Altwegg and Nichols, 2019; Field et al., 2007). This is a major impediment both to the reliability of monitoring results, and the extent to which they are actually used within conservation management. More specifically, it is important to define beforehand the particular management decisions that ranger-collected data might inform, so that these data are better integrated into decision-making processes (Nichols and Williams, 2006). This was a theme that cut across a number of the Chapters in this Thesis. Chapter 6 sought to elicit from park mangers the main purposes to which they currently put ranger-collected data, while Chapter 3 demonstrated an approach for one of the most common uses of these data (to identify poaching hotspots). Chapter 4 demonstrated how the performance of ranger-based monitoring in capturing trends in poaching depends to a large extent on the particular question being asked of monitoring data, in other words, the type of poaching trend managers hope to be able to detect.

To be effective, monitoring in conservation must not be considered an end in itself, but must be clearly integrated within a broader decision-making framework (Nichols and Williams, 2006). Knowing why and how data will be used aids the efficiency and usefulness of data collection. Alongside ensuring power to detect trends of interest, Field et al. (2007) argue that clear objectives are perhaps the most important aspect of monitoring – what exactly to measure, what level of change the programme seeks to capture, and so on. Altwegg and Nichols (2019) provide a good illustration of the importance of clearly defining the questions that conservation managers and others plan to ask from monitoring data. They use a case study of the South African Bird Atlas project, through which data on bird distribution and abundance are collated by citizen science birdwatchers. They highlight the importance of properly understanding the ultimate questions that are being asked of messy observational data. What kinds of questions do biodiversity managers and policy makers have around bird abundance and distribution? Data collection strategies, and the methods used to analyse these data, need to be designed with these broader questions in mind (Altwegg and Nichols, 2019).

*My findings: clearer goals strengthen adaptive management, aid quantitative assessment of monitoring performance, and motivate data collectors*

In Chapter 6, one of the main factors identified as explaining why park managers do not systematically analyse trends in ranger-collected data to inform anti-poaching was the lack of clarity about the purpose of data-based adaptive management as promoted through the MIKE and SMART programmes. As one senior staff at the Zimbabwean wildlife authority remarked: "*Many of the managers may not even know why they are doing MIKE and why it is important*" (Chapter 5; national-level respondent 11). The added advantage of an adaptive management approach over traditional management approaches was not well-communicated to park managers in Mana-Chewore. A specific problem was the lack of examples of how analysis of ranger-collected data could inform particular questions that were important to managers. In response to these findings, I sought to identify some specific examples and advantages of data-based management in the context of Mana-Chewore (Chapter 6: Table 6.3). Then, in the theory-of-change for ensuring optimal use of ranger-collected data, I identified as a key outcome that managers understand and take ownership of specific ways that analysis of trends in ranger-collected poaching data can inform their anti-poaching strategies (Chapter 6: Fig. 6.6). These results and the consequent solutions emphasise the importance of beginning with the end in mind - connecting monitoring data to specific management decisions.

The virtual ranger simulations of Chapter 4 further stress the importance of clearly defined goals for monitoring. I showed that the suitability and power of ranger patrols for detecting underlying trends in poaching depended on the particular question or goal of the manager. For example, are managers interested in detecting spatial or temporal patterns in poaching, or both? Is the goal to detect large changes in poaching, or is the detection of small changes equally important? What degree of confidence in trend detection (i.e., statistical power) are managers willing to accept? Are managers more interested in detecting annual or seasonal changes in poaching? The value of ranger-collected data to managers will vary depending on the answers to these, and many other similar, questions. For example, ranger-collected data on elephant poaching in Mana-Chewore tended to perform better at reliably detecting spatial patterns in poaching than temporal trends. Furthermore, clarifying the specific objectives of monitoring also clarifies the strategies required to meet these objectives. For example, I showed in Chapter 4 that whether or not increasing patrol effort leads to improved temporal trend detection depends strongly on the magnitude of the change in underlying poaching level over time.

Clarity on the purpose of collecting monitoring data may also help motivate data collectors, as my interviews with rangers showed in Chapter 6. One ranger remarked, '*We are the ones who collect, so we want to know, the data we are collecting, where is it going and how it helps us?*' (Chapter 6: ranger 9). Analysis of ranger responses across multiple questions suggests that a large proportion of the rangers in Mana-Chewore would be more focussed and engaged in data collection if they knew how their data would be used by park managers (Chapter 6: Fig. 6.5). While some rangers may collect data purely out of duty without concern about the specifics of data use, my results suggest that, on balance, the quality (consistency, detail, etc.) of patrol data is likely to be improved when rangers appreciate the purpose of these data. This has parallels with citizen science programmes, in which data collectors want to feel that they are contributing to clear outcomes (Jones et al., 2018).

*Future priorities for integrating monitoring and decision-making*

Looking ahead, multiple stakeholders (researchers, park managers, monitoring programme designers, and data collectors themselves) would all benefit from clearly defined goals for monitoring. There is a need for stakeholders to engage with each other to define these goals together. It is then that one can properly design monitoring to meet these objectives or assess the power of current monitoring designs. Monitoring is only worthwhile if managers are likely to change their practices in response to monitoring results (Field et al., 2007). In their review of global biodiversity monitoring, Jones et al. (2011) argue that the most valuable biodiversity indicators are those whose integration with decision-making is clearest.

An area where the goals of monitoring are often very clear is the monitoring of species targeted by trophy hunters. Here the goal of monitoring is to provide data on target species abundance over time to better understand its response to hunting pressure, and to guide the development of management strategies that optimise both revenue and sustainability. As an example, Kinahan and Bunnefeld (2012) assessed the performance and cost-efficiency of different strategies for monitoring mountain nyala abundance in order to inform the setting of hunting quotas. The goal here was to detect changes in nyala population numbers with reasonable power and meaningful precision. Similarly, Edwards et al. (2014) developed a novel index of the relative abundance of lions (the number of hunting days required to kill a lion) and showed that it could be reliably used to set sustainable quotas despite uncertainties in observation and lion population dynamics. Granted, the goal here is relatively simple (to detect changes in a single species population over time), but the trophy hunting case study nonetheless illustrates the power of monitoring when goals are clear.

Finally, there is a need to better incorporate budgetary considerations when designing and assessing monitoring programmes. Increasing the reliability with which monitoring data can meet specific objectives often involves increasing sampling coverage or frequency, which inevitably comes at a cost. Nuno et al. (2015), for example, show a sharp trade-off between monitoring effectiveness and cost for arial surveys of ungulates in the Serengeti. This raises the difficult challenge of properly assessing the ‘Value of Information’, that is, quantifying how additional investment in monitoring will improve management outcomes (Canessa et al., 2015). Managers and other stakeholders must decide whether gains in monitoring effectiveness are worth the cost. Such an analysis of cost efficiency was not explicitly considered in my Thesis, and I hope it will be a focus of my future work. Being more explicit about monitoring costs may actually help researchers and managers clarify realistic monitoring goals, thus ensuring monitoring results are more likely to ultimately aide decision-making.

## 7.5. The role of ranger-based monitoring in biodiversity conservation

*Key questions on ranger-collected data as conservation evidence*

In this Thesis I sought to evaluate the reliability and conservation value of ranger-based monitoring, using an in-depth case study of ranger-collected data on elephant poaching in Zimbabwe. Perhaps the most important practical outcome of my research is its contribution to the discussion around the role of ranger-based monitoring in biodiversity conservation more generally. The importance of baseline ecological and social evidence, like species population trends or poaching rates, for improving conservation management is already well established (Gillson et al., 2019). Furthermore, the review of the literature presented in Chapter 1 highlighted several examples of ranger-collected data informing conservation management in different contexts. However, I found only limited previous research that explicitly focussed on the reliability of ranger patrols for capturing particular trends of interest (Keane, 2010), and the factors affecting whether and how managers use these data to inform their decisions (Gray and Kalpers, 2005). I also found that the advantages of ranger-based monitoring are described in the literature in very general terms or with reference to a particular research case study where ranger-collected data were used, as opposed to being specifically investigated (see for example Ihwagi et al., 2015 and Moore et al., 2018). Therefore, it is still worth asking: is ranger-based-monitoring an appropriate means of contributing to the evidence base for conservation management? If so, how can ranger-based monitoring best be leveraged, what kind of evidence can it contribute, and in what way? What do the insights I have gained through my case study suggest concerning the role of ranger-based monitoring in biodiversity conservation?

*The elephant that is not in the room: power to detect trends*

Perhaps the most obvious part of answering these questions is a critical assessment of the power of ranger patrols to reliably detect management-relevant trends in species abundance and threat. Field et al. (2007), considering monitoring more generally, argue that such an assessment is the first step towards making monitoring meaningful, lamenting that millions of dollars are spent on monitoring that has no real chance of detecting changes in variables of interest. This was the major focus of the virtual ranger simulations of Chapter 4, and the results were somewhat sobering. The challenge is that ranger patrols, like all monitoring methods, cannot detect everything. Simulations showed that many elephant carcasses were inevitably missed - the elephants that apparently are not in the room but actually are. Under favourable conditions of wide patrol coverage and relatively high baseline levels of poaching (90 elephants per year or 3% of the population), smaller temporal changes in poaching (25% difference from the baseline) were almost impossible to detect even with high levels of patrol effort. Larger changes in poaching (50%) were more detectable but required high levels of effort (12 or more 7-day patrols per month). Only very large (75%) changes were detectable with low patrol effort. However, when baseline poaching was rarer (30 elephants per annum or 1% of the population), even very large changes in poaching were almost impossible to detect. Increases in poaching were also markedly more difficult to reliably detect than decreases, suggesting that ranger-collected data may not perform well at flagging a growing poaching threat (increases only became statistically apparent after 2 years). The ability of ranger patrols to adequately capture underlying spatial patterns in patrols was more promising, with moderate to high levels of spatial overlap between actual and detected poaching possible with medium levels of patrol effort in most scenarios. It turns out that spatial trend detection is less vulnerable to the effects of small sample sizes that were a major driver of the poor temporal trend detection results summarised above.

A notable result was that spatial bias in patrols, where rangers preferentially target areas where they have previously detected carcasses, had only very small effects on spatial and temporal trend detection. This is important because such targeted patrolling is perhaps the biggest criticism of the ability of ranger-based monitoring to produce reliable results (Moreto et al., 2014; Stokes, 2012). It turns out that targeting only biases results in contexts where the underlying spatial pattern of poaching is highly clustered. Given the complexity of factors that may influence poacher behaviour, and how these vary in time and space, more spread-out distributions of illegal activity may in fact be more common than concentrated clusters (Beale et al., 2017; Rashidi et al., 2015), so this concern may be overstated. Overall, however, my results suggest that caution is needed when relying on ranger-collected data to capture trends in poaching over medium time scales (1-3 years). There is significant uncertainty in the power of patrols to capture these trends, and this power is very sensitive to the particular trend of interest and the broader poaching and patrolling context (i.e., patrol coverage and the baseline poaching level). My results are also specific to elephant poaching, which is a relatively less common illegal activity. Bushmeat hunting, for example, is likely to occur at magnitudes far higher than 90 incidents per year (the baseline poaching rate used in my virtual ranger simulations) (Gandiwa et al., 2013). Similarly, the collection of data on species abundance while on patrol will likely involve far higher sample sizes, and therefore more promising results in terms of the power to detect trends (Gray and Kalpers, 2005).

Data scarcity remains a concern, however, hindering trend detection and data reliability. There is a need to investigate strategies for boosting detection rates, such as patrols informed by community-based intelligence (Cooney et al., 2016). Also, in areas where sport hunters cover wide areas within protected areas (as in Chewore), detections from sport-hunting patrols could supplement those from regular ranger patrols. In the future, detections by rangers may also be boosted by the use of novel technologies such as unmanned aerial vehicles (Gonzalez et al., 2016).

*Begin with the end in mind: longer term trends or immediate intelligence?*

As highlighted in section 7.4, monitoring programmes can only be properly assessed if their goals are clear. Careful consideration must be given to the particular decisions that ranger-based monitoring might inform in a particular context. There are numerous possible uses to which ranger-collected data may be put, and the value of these data must be considered in light of these end-uses. The virtual ranger simulations considered the detection of spatial and temporal trends in poaching over the medium term, using 2-3 years' worth of ranger-collected data. What about the use of ranger-collected data for more immediate indications of changes in poaching across time and space? Chapters 5 and 6 revealed that both rangers and managers are mainly concerned with these shorter-term patterns, and that they see the value of ranger-collected data mainly in terms of its ability to provide this more immediate "intelligence". Data use was basic and reactive, with information from one patrol guiding the next few patrols, *"soon after the patrol we gather for a debriefing, that's where we extract some important* *information [observations from patrol] that will assist us in the planning our next patrols*" (Chapter 6: manager 2). Similarly, in her review of the role of ranger-based monitoring in tiger conservation across 8 sites, Stokes (2010) suggests that ranger-collected data is most useful for flagging the short-term presence/absence of illegal activities so that managers can respond directly to present threats. She suggests that longer-term trends (>1yr) from these data are less useful because of variations in detectability and patrol effort in time and space.

Gray and Kalpers' (2005) case study in the Virunga-Bwindi region of central Africa demonstrates the wide uses to which ranger-collected data can be put, including (but not limited to) both immediate intelligence and longer-term trend detection. Rangers' observation at their site helped populate a comprehensive database of individual gorillas, their family groups, and their home ranges. Ranger-collected data on illegal resource extraction was also used to guide law enforcement in real-time, as managers responded to immediate threats. Also, managers and researchers were able to identify seasonal and annual trends in common illegal activities such as bushmeat snaring and bamboo cutting by using ranger detections of these activities adjusted for patrol effort variation. Whilst the reliability of these trends was not formally assessed, they provided, at the very least, a good qualitative understanding of the nature and intensity of threats. Finally, ranger-collected data has also furthered research on gorilla ecology and behaviour. In other contexts, the goal of ranger-based monitoring may be more focussed, such as tracking the numbers of a species of distinct conservation value. O'Neill (2008), for example, developed strategies for robustly monitoring saiga antelope population numbers in Russian protected areas via ranger-conducted vehicle transects.

Sometimes the goal for monitoring may simply be to give managers a qualitative sense of trends of interest. Addison et al. (2015), for example, showed that marine protected area managers in Australia assess the condition of marine ecosystems by qualitatively judging the direction of trends in various species from quantitative monitoring programmes. In my case study of Mana-Chewore, managers may not need statistical models of the distribution of poaching in space, but rather a more qualitative sense of which parts of a protected area are particularly vulnerable to poaching. The results of Chapter 6 showed that managers in Mana-Chewore pin the locations of ranger-detected elephant carcasses and poacher camps/spoor on a physical map and develop a good sense of vulnerable areas based on previous encounters. Similarly, statistically significant differences in poaching levels from one year to the next (which was the criteria used in the virtual ranger simulations developed in Chapter 4) may be less important to managers than would a broad qualitative understanding of trends in poaching (i.e., increasing, decreasing, or constant). The danger here is that these qualitative patterns may be misleading, identifying trends and patterns in poaching that may not reflect the underlying reality. Ranger-collected data may also be used to establish the simple presence or absence of threats over different spatial or temporal scales (e.g., per month, or per region of a park), which may be less susceptible to the uncertainties associated with strict trend detection (Earle, 2016).

The case studies reviewed here, and my own results, show that ranger-collected data may perform very differently according to the particular monitoring objective, again emphasising the importance of beginning with the end in mind.

*Partnerships to unlock the potential of ranger-collected data*

Many of the ranger-based monitoring case studies reviewed above involved partnership between managers and some external agency. The Virunga gorilla case study depended heavily on resources and training from a partnership of three external NGOs (Gray and Kalpers, 2005). Similarly, in the saiga antelope monitoring study (O'Neill, 2008), extremal researchers were needed to design ranger-based monitoring strategies that accounted for variations in monitoring intensity and spatial coverage. Also, the improved law enforcement effectiveness of ranger patrols in Queen Elizabeth National Park relied on a sophisticated statistical analysis of trends in illegal activities carried out by expert scientists (Critchlow et al., 2016). Finally, my own case study further demonstrates the potential of partnerships for gaining deeper insights from ranger-collected data – identifying spatial patterns of elephant poaching required complex statistical modelling and careful parameterisation (Chapter 3; Kuiper et al., 2020).

In Chapter 6, park managers as well as senior staff of Zim Parks (the national wildlife authority) suggested that analysis of trends in ranger-collected data should be the responsibility of the scientific division of the organisation. Zim Parks employs scientists ('ecologists') to work both at the local and national levels, and respondents suggested that these individuals are better trained and able to interpret and analyse poaching data. Managers also suggested that ecologists could advise them on management actions based on their analyses, *"I think the research guys have the responsibility to analyse the data, and then give us advice. If they need the data, we can provide it."* (Chapter 6: manager 9). Unfortunately, I did not find any evidence of such collaboration between managers and scientists at my case study site. In a similar vein, senior staff of the MIKE programme described a recent effort to develop an online dashboard for automating the production of simple summaries, graphs and maps of elephant mortality records submitted to MIKE. The goal is for park managers at individual MIKE sites to log in and access already-analysed data. Indeed, a few of the park managers I interviewed expected more feedback from MIKE on trends in elephant poaching based on the data they submit to the programme. Finally and more generally, specialised technical expertise are often required to quantify and properly account for the various biases in ranger-collected data highlighted throughout this Thesis (Dobson et al., 2020).

Park managers and rangers have diverse responsibilities and rightly focus their efforts on practical conservation action. The design, funding, and maintenance of ranger-based monitoring programmes, and the analysis of outcomes, may therefore be best achieved in partnership with external conservation and research organisations.

*Are monitoring and law enforcement complementary?*

An important consideration is how data-collection on patrol fits in alongside other ranger duties such as anti-poaching and law enforcement, as this will determine the sustainability and consistency of monitoring. Indeed, this is the main way that ranger-based monitoring differs from many other forms of monitoring – it is relatively opportunistic. Ranger patrols serve various functions, perhaps the most important of which is law enforcement and wildlife protection, particularly the deterrence and apprehension of illegal resource users and hunters (Belecky et al., 2019; Critchlow et al., 2016). These functions are achieved through surveillance – covering wide areas within protected areas in order to monitor key resources and ensure their protection. Ranger-based monitoring, or law-enforcement monitoring, falls within this broader purpose. How data collection on patrol relates to the broader law enforcement function will vary. In her case study of ranger-based monitoring of tiger abundance and threats in Asia, Stokes (2010) suggested that data collection can overburden rangers and distract from law enforcement. O'Neill (2008) also argues that ranger-based monitoring strategies cannot be made too complex as this might compromise their ability to fulfil their main role of deterring illegal activity (in her case saiga antelope poaching).

In my case study, however, I found that monitoring and law enforcement were complementary. As one ranger remarked, *"The purpose of patrols is to collect data, and to prevent the animals from being killed by illegal hunters. Monitoring and anti-poaching work hand in hand, because when I am collecting data, that data can lead me into apprehending a poacher, or lead me into knowing how the poachers are moving*" (Chapter 5: ranger 13). Granted, ranger-collected data in Mana-Chewore was mainly used to inform short-term and reactive patrol strategies. Nonetheless, rangers consistently recorded and reported elephant poaching and other data while on patrol, seeing it as complementary to their broader work and important for their supervisors. The longer term databases formed in this way can be invaluable for law enforcement. Critchlow et al., (2016) provide an excellent example of this, where long term ranger-collected data on several forms of illegal resource use in Queen Elizabeth National Park were used to predict hotspots of illegal activity and guide future patrols, leading to large increases in detection and law enforcement efficiency. Thus, managers in some contexts will need to make compromises between monitoring and law enforcement, whereas in others, pursuing both may be complementary. Importantly, even if patrols are strictly focussed on law enforcement, opportunities for data collection while on patrol may still exist. valuable monitoring data may still be collected. Also, when poaching threats are low, ecological monitoring may provide rangers with a rewarding and meaningful activity. If rangers have nothing to report, motivation levels might drop (Mesterton-Gibbons and Milner-Gulland, 1998)

*Future priorities for ranger-based monitoring*

Priorities for future research and practice in the area of ranger-based monitoring flow from the sections above. It is important that stakeholders acknowledge how difficult it can be to reliably detect trends in species abundance and threat from ranger-collected data, and to separate real trends from those driven by patrol bias. Yet, because data collection is often incidental to the law enforcement element of patrols, it is uncommon for managers to think carefully through such considerations. It is all too easy to take patterns in ranger-collected data at face value, without thinking about the underlying processes generating these data. Greater clarity is needed on the particular ways in which managers hope to use ranger-collected data, so that patrol strategies can be designed to meet these objectives with reasonable certainty. My results, and the broader literature, also suggest that organised partnerships between park managers and other key stakeholders like NGOs and scientists are often necessary to properly unlock the potential of ranger-based monitoring. Also, the qualitative interview findings in

Chapters 5 and 6 underscore the importance of engaging ranger and manager perspectives, and understanding their work context and priorities, when designing monitoring programmes and setting monitoring goals.

This DPhil research considered a relatively small number of examples of the use of ranger-collected data with a specific focus on elephant poaching. There is a need for future research to explore the potential of ranger-collected data to answer a broader array of questions in other conservation management contexts. As discussed above, there are very few studies that focus on the design and advancement of ranger-based monitoring as a conservation tool. Looking ahead, one of the key advantages of ranger-based monitoring is that some form of patrolling and surveillance is one of the most basic law enforcement activities in protected areas, and it can function well with minimal external investment and planning. Opportunistic data collection on patrol is therefore both cost-efficient and sustainable. Finally, the relevance of ranger-collected data may be influenced by the increasing accessibility and reliability of remote monitoring technologies, such as drones, acoustic sensors, satellite imagery and light detection and ranging (LiDAR) technology (Astaras et al., 2020; Davies et al., 2014; Gonzalez et al., 2016).

## 7.6. Conclusion

In Chapter 1, I identified the discrepancy between what rangers observe and reality (observation uncertainty), and the motivations and priorities of the rangers and park managers who are tasked with implementing ranger-based monitoring (implementation uncertainty), as key factors influencing monitoring and management success. These uncertainties must be understood and addressed if ranger-based monitoring is to make an effective contribution to the evidence base for conservation management. The aims of this research were to assess (a) the reliability, and (b) the management use of ranger-collected data, using the monitoring of elephant poaching in Zimbabwe as a case study. In Chapter 3, I sought to address a management question that is commonly asked of ranger-collected data, that is, which areas are more vulnerable to poaching? I used participatory modelling and statistical methods to account for biases in ranger observations of poached carcass locations for more robust inference in the face of uncertainty. This Chapter thus contributed to both my research aims (data reliability and use). Next, I sought to understand how different features of the ranger patrol observation process interacted with underlying poaching dynamics to influence the power of patrols to capture spatial and temporal patterns of poaching. This analysis revealed specific factors affecting data reliability, which was also strongly contingent on the particular management questions asked of ranger collected data (again contributing to both research aims). Next, in my first qualitative analysis, I used interviews to identify factors affecting how engaged rangers were with patrol-based data collection and outlined ways for fostering greater motivation for monitoring, thus addressing a key component of implementation uncertainty. In my final data Chapter, I identified several factors influencing the limited extent to which park managers have adopted adaptive management in Mana-Chewore and developed a theory of change for optimising the management use of ranger-collected data to inform anti-poaching strategies.

My final overarching research question was to identify how the insights gained from these four data Chapters could be used to maximise the contribution of ranger-based monitoring to protected area management. Clearly defining monitoring and trend detection goals is an essential first step in which all stakeholders should be involved – it is particularly important that rangers and park managers co-develop and buy-in to these goals. Park managers must feel confident about how identified trends can inform specific management actions (such as changing the spatial pattern of patrols or employing alternative anti-poaching strategies). This must be followed by critical evaluation of the likelihood of achieving monitoring goals, and explicit effort to acknowledge, measure, and account for the uncertainty in ranger-collected data. Data collection strategies can then be designed that are not only useful, but robust to uncertainty. Partnership between park managers, external organisations, and scientists can help facilitate better management through the use of ranger-collected data, such as by providing the technical resources and expertise for analysing and interpreting these data robustly. Hundreds of thousands of wildlife rangers patrol protected areas globally, regularly encountering plant and animal species and evidence of human threats to them. These data, if collected and used well, can have a crucial role to play in bolstering the evidence base for biodiversity conservation.

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# Appendices

## 1. Appendix 1: R code for the virtual ranger simulations (Chapter 4)

General notes on code:

1. Below is the code for the main virtual ranger function. This function can be called using different sets of parameter values according to the scenario in question.
2. The function runs the simulations for a number of time steps [timesteps], in each step carcasses are generated and then distributed in space. Next, patrols are simulated in space, detecting a certain proportion of carcasses.
3. The model repeats the run through these time steps for each replicate (i.e. [nreps] times). There are thus two main for-loops - the outer one for replicates, the inner one for time steps. Because the loops involve random variables for carcass generation and detection, the results will be slightly different for each replicate. Thus, the mean and SD values can be calculated from all reps.
4. There is also another nested loop for the different carcass age classes, which closes and opens again to avoid unnecessary computation
5. Finally, various outputs are produced – such as the number of carcasses poached and detected in every park grid cell in every time step.

Code:

```
vr.func<-function(
  #Starting values------------------------------------------------------------------------------------------------------

  #Landscape, timesteps, replicates
  ncells=712, # the number of grid of cells over Chewore created in the "creating Chewore grid" script
  timesteps=60,burn=24,
  nreps=50, # set the number of replicates

  #carcass numbers and distribution:
  popsize=3000,
  rp=0.05,
  sd.p=0.005, # the SD of the poaching rate
  rn=0.02,
  space.time=FALSE, #whether there is space time variation in poaching or not
   aggrParam=2.73, # baseline aggregation parameter derived from the real study area poaching
hotspot raster map
  #generated in chapter 1
  hotspots.p='med', # the level of clustering/aggregation of carcasses (high, medium, low),
  # Medium corresponds to baseline aggr
  aggrN=5,# spatial aggregation of natural mortalities
  pers=48, # how long a carcass persists for

  #parameters for simulating change in poaching
```

```
  p.trend="no",
  start.trend=burn+12,
  p.change.level=0.50, # the proportional change in poaching to be simulated
  p.change.period=60, # the period  over which that decline happens (in months)
  end.trend=start.trend+p.change.period,
  #tthe using the equation X^(n)*P = 0.5*P. Where X is the monthly change in poaching. X - 0.5^ (1/n)

  # Patrols
  numpat=6, # the number of patrols per month
  prop.pat.rand=0.25,
  sizepat=15, #how many 5km2 cells eacxh patrol takes up
  x=0.6, low=0.5, # these control the shape of individual 7-day patrols (see in code below):
  # lower values = more spread out away from base, higher values = patrols concentrate near base
  mlen=48,
  dpP=0.5,dpN=0.5,
  constrained.pat=FALSE,
  rate.det=0.10,base.det=0.78,
  pat.vary=FALSE,pat.CV=0.5,pat.step.change=F,

  #intelligence and hunting
  hc.extra=T,
  prop.extra=0.20
){

  #Derive extra model parameters from main parameters specified above:
  steps.per.year=12; nyears=timesteps/steps.per.year;
   if(hotspots.p=='med'){aggrP=aggrParam}else{if(hotspots.p=='low'){aggrP=aggrParam*5}else{aggr
P=aggrParam*0.2}}#last option is high
  if(hotspots.p=="high"){h.level=1}else{if(hotspots.p=="med"){h.level=2}else{h.level=3}}
  hot.levels=c("high","med","low")
   p.change.month=p.change.level^(1/p.change.period)  #  test:  0.5*(p.change.month^36)  (correct  =
aprrox 0.25)

  #storage for outputs----------------------------------------------------------------------------------------------------
  # 3D arrays for storing the number of carcasses of each type in each cell in the landscape, at each
time step, and for each replicate
  # arrays with three dimensions: [rows=cells,columns=timesteps, different matrices=replicates]

  #first create the names foir the dimensions of the arrays
  repnum<-vector();for(i in 1:nreps){repnum[i]<-paste0("rep",i)}
  timenum<-vector();for(i in 1:timesteps){timenum[i]<-paste0("t",i)}
  cellnum<-vector();for(i in 1:ncells){cellnum[i]<-paste0("cell",i)}
  agecat<-vector();for(i in 1:pers){agecat[i]<-paste0("a",i)}

                                                                                                    numpcell<-
array(data=NA,dim=c(ncells,timesteps,nreps),dimnames=list(cellnum,timenum,repnum))
  # example for sub setting the above array:
  # numpcell['cell34','t60','rep1','a3']; numpcell[,'t60','rep10'];
  # numpcell[,14,5] # this is the number poached carcasses in each cell for time step 14 and replicate
5

  #arrays for storing number available and detected
                                                                                                  numavpcell<-
array(data=NA,dim=c(ncells,timesteps,nreps,length(agecat)),dimnames=list(cellnum,timenum,repn
um,agecat))
                                                                                                 numdetPcell<-
array(data=NA,dim=c(ncells,timesteps,nreps,length(agecat)),dimnames=list(cellnum,timenum,repn
um,agecat))

                                                                                              numdetPcell.hc<-
array(data=0,dim=c(ncells,timesteps,nreps),dimnames=list(cellnum,timenum,repnum))

  # Matrix indicating which cells are patrolled in each time step in each rep:
```

```
  patrols<-array(data=NA,dim=c(ncells,timesteps,nreps),dimnames=list(cellnum,timenum,repnum))

  #Vectr to store the monthly poaching rate:
  rp.m<-array(data=NA,dim=c(timesteps,nreps),dimnames=list(timenum,repnum))

  ######------------Setting up model of the distribution of poached carcasses across space------------
#######

  ##First INITIALISE the number and distribution of carcasses of different ages in timestep 1
  # (number of carcasses already in the landscape, per cell and age, when the simulation starts)

  ##########Here is the exponential decay function of DP as a function of carcass age-------------

   rate.decline=rate.det #these are parameterised from the real age versus detection data (see
separate script)
  base.det = base.det #parameterised from the real age versus detection data (see separate script)
  dp.func<-function(age){
    dp<-base.det*(1-rate.decline)^age #simple exponential decay function
    return(dp)
  }
  dp.v.age<-dp.func(1:48)

  #see what the relationship looks like:
  # par(mfrow=c(1,1),oma=c(0,0,0,0),mar=c(5,5,2,2))
  # plot(y=dp.v.age,x=1:48,ylab="Detection probability",xlab="Age carcass (months)",
  #      cex.lab=1.8,pch=19,cex.axis=1.5,ylim=c(0,0.70))

  ##########Here is another exponential decay function, but for probability of a cell being patrolled
  ##########as a function of distance to ranger camp in meters

  mx<-0.75   # RH asymptote (i.e. maximum probability of patrol - near camp)
  mn<--0.1  # LH asymptote (lowest dp)
  cc<-0.4 # scale parameter controlling rate of change
  d<-12  # curve midpoint (month by which detection probability has halved)
  constrained.pat.func<-function(distance){
    probpat<-mx-((mn+mx)/(1+(exp(cc*(d-distance)))));return(probpat)
  }
  constrained.pat.vec<-constrained.pat.func(1:30)
  # par(mfrow=c(1,1),oma=c(0,0,0,0),mar=c(5,5,2,2))
   # plot(y=constrained.pat.vec,x=1:30,ylab="Probability of patrol",xlab="Distance to main ranger
station (km)",
  #      cex.lab=2,pch=19,cex.axis=1.3,ylim=c(0,0.80),type="l",lty=1)

   #Now these are the probabilities of  cell being patrolled, determined by their distances from the
main stations
  # the distance to camp for each cell has been calculated in a separate script
  dist.camp.df$prob<-constrained.pat.func(dist.camp.df$dist.camp)

  #set up an array to store for timestep 1, the number of carcasses of different ages available in each
cell
                                                                                        init.p.cell<-
array(data=NA,dim=c(ncells,length(agecat),nreps),dimnames=list(cellnum,agecat,repnum))
  # the below nump.av takes into account that over time (age classes) the poached carcasses will be
detected, so those
  # carcasses of higher age will be fewer as some will have been detected since poached
  nump.av<-numeric()

   #####------------------------Setting up space time variation scenarios-------------------------------------
###########

  mat.hot<-array()
  # Note if there is no space time variation, we simply use the mat.hot matrix above
  if(space.time==FALSE){
```

```
    mat.hot<-mat.hot.no.st[,1:timesteps,1:nreps,]
  }else{
    mat.hot<-mat.hot.st[,1:timesteps,1:nreps,]
    ############(2) Scenario 2: parameterised based on space time variation in the actual data

   #NOTE: this uses the data from the space-time analysis of 96 fresh and recent carcasses recorded
between 2010
    #and 2015 at the case study site (Chewore)

    #This gives the probabilities for each cell receiving a carcass for each time step. Note that the
probabilities change every 6 months
    #This is based on the pixel values of hotspot maps based on real caracss data for each 6 motnh
period
    #So each 6 months, different parts of the park have the highest probability of receiving a carcass.

    #Note it remains probabilistic as we are using the probabilistic sample function below
  }

  for(r in 1:nreps){
    for(a in 1:pers){ # looping through the different carcass age classes
      rp2<-rnorm(n=1,mean=rp,sd=sd.p) #the poaching rate is allowed to vary slightly around a mean
      if(rp2<0){rp2=0}
      nump<-round(popsize*rp2*(1/steps.per.year),0);nump
      # here is the key line below: the number of those paoched that are still available at age=a will be
a decreasing
       # function as those poached are gradually detected in the timesteps before model runs. We
simply use the detection
       # probability versus age function used elsewhere as the relationship will be roughly the same
(note that this function
      # was actually created for a different purpose, to measure how detectable caracsses of different
ages are)
      nump.av[a]<-round(dp.func(a)*nump,0)
      aggr<-aggrP;mu<-nump.av[a]/ncells; nbp<-aggr/(aggr+mu)
      aa<-rnbinom(n=ncells,size=aggr,p=nbp);aa<-aa[order(-aa)];sum(aa)
      init.p.cell[,a,r][mat.hot[,a,r,h.level]]<-aa
      # ordered by cell number and with the nbinom vcalues in the coorect place
      # note the mat.hot matrix is used, at the relevent hot.spot level 'h.level'
    }
  }

  # Check if working:
  # apply(init.p.cell[,,1],2,sum)
  # all<-apply(init.p.cell[,1:48,r],1,sum) #sum of total number of carcasses of all ages
  # st<-st_sample(grsf, size=all,type = "random", exact = TRUE);plot(chewore);plot(st,add=T)

  #note later below, we will set each of these initialised carcasses to gradually dissapear (i.e. set the
to different ages)

  # ###Here we set the time steps in which random patrols are conducted (as oppossed to biased
patrols):
  #versus biased patrols:
  tsteps.rand<-sample(1:timesteps,round(prop.pat.rand*timesteps,0),replace = FALSE)

      ###############################----START OF SIMULATION MODEL------
#################################################################################

  start_time <- Sys.time() # record the time at which the code starts running (to see time length)
  #r=1;t=1
  for(r in 1:nreps){ # START OF THE REPLICATES LOOP

    ###For the scenario with step changes in patrol effort---------
    # we need to set the timestep after which the step change occurs, and the degree of change,
    #for each replicate and AVOID setting these values for every time step.
```

```
  #Hence we have it here in the r loop but not in the t-loop
  # (could achuieve the same by opening and closing loops below)

  if(pat.step.change==TRUE){
   tt<-sample(x=seq(burn+1,timesteps),size=1);tt#time step when the step change starts
   step.change=sample(x=c(0.50,2),1);step.change #whether the step change is up or down
  }

  for(t in 1:timesteps){ # START OF THE TIME STEPS LOOP
   print(paste0("trend=",p.change.level,"eff=",numpat,"rep=",r,", month=",t))

   ################################################################
   ################### (A) CARCASS GENERATION MODEL###############
   ################################################################

   if(p.trend=="no"){
    rp.m[t,r]<-rnorm(1,mean=rp,sd=sd.p)# the poaching rate allowed to vary 25% around true# the
poaching rate allowed to vary 25% around true
   }else{ #if there is a change in poaching over time
    if(t<start.trend){rp.m[t,r]<-rnorm(1,mean=rp,sd=sd.p)}

    if(t==start.trend){rp.m[t,r]<-rp}
    #Now simulate the change in poaching starting from after the start of the trend:
     if(t%in%c((start.trend+1):end.trend)){ #start.trend is the timestep when the trend simulation
starts
     mean.decline.at.t<-rp*(p.change.month^(t-start.trend))
     rp.m[t,r]<-rnorm(1,mean=mean.decline.at.t,sd=sd.p)
    }
    if(t>end.trend){
     rp.m[t,r]<-rnorm(1,mean=rp*(p.change.month^(end.trend-start.trend)),sd=sd.p)
    }
    if(rp.m[t,r]<0){rp.m[t,r]=0.01}
   }
   # rp.m[60:120,1:5] # test to see if working as expected

   # total umber of poached and natural carcaasses generated in each time step
   rp2<-rp.m[t,r]
   nump<-round(popsize*rp2*(1/steps.per.year),0);names(nump)[1]<-"nump";nump

   #### Now need to assign these carcasses to each cell in the park--------------------------------------
----------

   if(hotspots.p==0){
     # Here carcasses are (1) distributed randomly in the landscape PLUS (2) there is no space-
time dependence
    # (1) is achieved with a random sample
     # (2) is achieved because, each time step, generated carcasses are distributed in a new way
and therefore
    # do not depend on where caracsses where in the previous time step

    cellsp<-table(sample(1:ncells,size=nump,replace=T));index<-as.numeric(names(cellsp))
    numpcell[,t,r]<-rep(0,ncells);numpcell[,t,r][index]<-cellsp
   }

   # We now simulate hotspots of poaching, with three scenarios of different levels of aggregation
(clumping)
  # the average scenario (based on parameterisation), and then a more and less clumped scenario
   if(hotspots.p%in%c('low','med','high')){
    ##### HOTSPOPT SCENARIOS-------------------------------------------------------------------------------
-------------------------

     # Here carcasses are distributed to cells in a clumped way by using the negative binomial
distribution (NBD)
```

```
# and changing the aggregation parameter (k/size parameter)
# note that the NBD is defined in ecology using the mean (mu) and the dispersion/aggregation parameter (size, or k)
# k = aggregation - smaller value means more aggregated (less dispersed). With higher K, mean approaches variance

# Note the below also generates carcasses in the SAME general places (cells) each time step (hotspots persist over time,
# because the same hotspot scores are used for the mat hot matrix each time step

aggrP=aggrP# the aggregation parameter for the NBD,
muP<-nump/ncells # mean number of carcasses per cell (mean parameter for NBD)
nbpP<-aggrP/(aggrP+muP) # NBD probability where size is the aggregation parameter k, and mu is the mean parameter

for(i in 1:100){
 # This below rbinom code does not lead to the EXACT right number of carcasses in each time step because we are
  # working with a random variable (the sum of carcasses in each cell in each time step does not always add
 # up to exactly the right number of available carcasses). This for loop runs the rbinom until the total number of
 # carcasses generated (sum of [aa] vector) is within 10% of the true number, and then breaks the loop and uses that vector
   aa<-rnbinom(ncells, # draw 1 value from the NBD for each cell in the park (ncells = 100 samples)
           size=aggrP, # this defines the aggregation parameter
           p=nbpP)# this is the NBD probability parameter
 if(abs(nump-sum(aa))<0.15*nump){break}
}
aa<-aa[order(-aa)];sum(aa)

 # The next key step is to assign the highest NBD values (counts of carcasses per cell) to PARTICULAR cells which are
# considered hotspot cells so that these cells can be THE SAME CELLS each time step. If we just ran the rbinom function
# each tome step, then DIFFERENT cells would get the highest counts in each time step.
# We do this by ordering the negative binomial values from lowest to highest, and then assigning these to the park cells
# according to the hotspot scores of the park cells (see the hotspot matrix mat.hot above)
#The mat hot matrix basically stores the cell rankings for each time step and each replicate, these rankings are based
# probabilistically on the hotspot scores (cells with highest hotspot scores are more likely to rank more highly)

numpcell[,t,r][mat.hot[,t,r,h.level]]<-aa
#this simply ensures the highest NBD realisations (highest single cell carcass numbers) are assigned to the cells
# that are ranked highest (in terms of hotspot intensity) for that time step
}
#working till here 17 April - new :)

#######END OF HOTSPOT SCENARIOS------------------------------------------------------------------------------------------------------

#######################################################################################
### (B) JOINT MODEL - available carcases after generation and detection##############
#####################################################################################

# The Core code to calculate the number of poached cells available in each time step:
```

```
    # we need to account for carcasses disappearing by  have a rolling sum of carcasses generates and detected ONLY in
    # previous X time steps, and exclude those from earlier. The rowSums function is great for this. The array npcell already
    # has timesteps as columns, cells as rows, so we get row sums (across columns) to get totals summed over timesteps
     # note we use special indexing to get the sum over a SET number of previous time steps (matching carcass persistence)
    # define [pers] as the number of time steps for which a carcass persists

    # numpcell[,1:3,1]# to illustrate, here is the number of carcasses generated for each cell for
    # each of first three timesteps
    # rowSums(numpcell[,1:3,1])# now simply add up the totals across the three time step columns.
    # t=1; r=1

    for(a in 1:pers){#all age classes
      if(t==1){

        # set up the loops in timestep 1 - determining the total number of carcasses available in each cell,
        # at each age

        numavpcell[,t,r,1]<-numpcell[,1,r] #these are the fresh carcasses (poached in time step 1)
         numavpcell[,t,r,2:48]<-init.p.cell[,2:48,r] #these are the carcasses of other ages available at t=1 (initialised)
        numavpcell[,1,1,23]
      }

      else{if(t>1&a==1){

       ##RUN this little but if there are HUNTING AND COMMUNITY INTELLIGENCE DETECTIONS

        if(hc.extra==T){ #only run this for the situation where a=1
          #t=1;r=1;prop.hc<-0.20
         tot<-sum(numpcell[,t,r]);det.hc<-round(prop.extra*tot,0)#number of elephants poached in this particular month
            gg<-which(numpcell[,t,r]>0) #these are the park cells where there was poaching in the particular time step
           gg2<-sample(gg,size=det.hc,replace=F) #select 20% of the cells with poached carcasses this month

          #Now fill the array of detected by hunting and intelligence:
          numdetPcell.hc[gg2,t,r]<-1 #one carcass was detected in each of these cells

          #Had this bit of code in error - should not have been removing poached carcasses
           #numpcell[,t,r][gg2]<-numpcell[,t,r][gg2]-1 #remove one  poached carcass from each of the selected cells
        }

        # fresh carcasses (age=1 or a=1) come in each time step according to poaching rate
         # The number of carcasses available  that are <1 month old is simply the number poached that month:
          numavpcell[,t,r,a]<-numpcell[,t,r] #so in time step 2, there will be numpcell[,2,r] carcasses generated (cells)

      }else{if(t>1&a>1){
        #t=2;a=3

        numavpcell[,t,r,a]<-numavpcell[,t-1,r,a-1]-numdetPcell[,t-1,r,a-1]

        # numavpcell[,,r,3]
        # sum(numavpcell[,t,r,a])
        # sum(numavpcell[,t-1,r,a-1])
```

```
    }
    }
    }
  }
  ######################################################################
  ###################(C) RANGER PATROL MODEL########################
  ######################################################################

  #####Varying patrol effort through time
  ##(1) Varying randomly from month to month

  if(pat.vary==TRUE){
    numpat.actual<-round(rnorm(1,mean=numpat,sd=pat.CV*numpat),0)# to give a CV of 50%
    #If numpat is zero or less, change it to 1
    if(numpat.actual<1){numpat.actual=1}
  }else{numpat.actual=numpat}

  ##(2) Step changes in patrol effort

  if(pat.step.change==TRUE){
    #NOTE: have already set tt (time step after which step change occurs)
    #and steop.change (degree iof change in effort) in the code lines above
    # see lines 230

    #For all time steps after tt, the new patrol effort is the old effort
    #multiplied by step change (step.change*numpat)
    if(t>=tt){numpat.actual=step.change*numpat}else{numpat.actual=numpat}

    #If numpat is zero or less, change it to 1
    if(numpat.actual<1){numpat.actual=1}
    numpat.actual
  }else{numpat.actual=numpat}

  #### Function for assigning each patrol to a cell in the landscape -----------------------------------------------------------

  # Scenarios:(1) patrols assigned to cells completely randomly
  #          (2) patrols are constrained to areas close to ranger camps
   #           (3) patrols are targeted: weighted based on where they found carcasses previously (learning process).

  # (1) start with a basic random sample (completely random cells patrolled): this gives the numbers of cells that receive a patrol
  if(t%in%tsteps.rand){ #if the current time step is one in which random patrols are conducted, then execute the below code
    if(constrained.pat==FALSE){
      patrolled<-sample(x=1:ncells,size=numpat.actual,replace=FALSE);patrolled #random sample (random patrols)
    }else{ #if patrols are constrained
      patrolled<-sample(x=1:ncells,size=numpat.actual,prob=dist.camp.df$prob,replace=FALSE)
    }
  }
  # (2) now a scenario where rangers patrol based on previous detections
  # use the number detected in the previous 12 time steps to weight cells

  # Intermediate step to illustrate: this gets, for each rep and cell, the sum of detections for first 12 time steps
  #numdetPcell[,1:12,1,1] # this selects all the cells in the first 12 time steps, and the first rep
  #apply(numdetPcell[,1:12,1,1],MARGIN=c(1),sum) # the sum of detected poached carcasses for each cell in first 12 time steps in first rep

   # the below code sums, for each cell and for the particular replicate, the number of carcasses detected in the previous
```

```
    # [mlen] time steps in that cell. It has an if statement to ensure the calculation is correct for the first mlen time steps.
     # (mlen is the length of 'memory' of the rangers - how long they take into account previous detections for.
    #mlen=24;t=17;r=1;pat.pattern=2

    if(!t%in%tsteps.rand){# if the time step is NOT one of the timesteps in which random patrols are conducted
      #---------------------------------------------
      if(t<13){ # NB, in the first 12 months not enough carcasses are detected to meaningfully assign probabilities to cell (very few
        # will actually have positive probabilities so the sample function below doesn't work)
        # Decided therefore to have a 12 month 'burn in' stabilisation period
        if(constrained.pat==FALSE){
          patrolled<-sample(1:ncells,size=numpat.actual,replace=FALSE);patrolled
        }else{#if patrols are constrained
          patrolled<-sample(x=1:ncells,size=numpat.actual,prob=dist.camp.df$prob)
        }
      }else{
        if(12<t&t<mlen){# (.e. when the time step is between 13th and mlen)
                                                            #numdetprev<-future_apply(numdetPcell[,1:(t-1),r,1:pers],MARGIN=c(1),sum);sum(numdetprev>0) #detected of all ages
            #numdetprev<-lapply(numdetPcell[,1:(t-1),r,1:pers],function(x){sum);sum(numdetprev>0) #detected of all ages
          numdetprev<-rowSums(numdetPcell[,1:(t-1),r,1:pers]);#sum(numdetprev>0) #detected of all ages<-lapply(numdetPcell[,1:(t-1),r,1:pers],sum);sum(numdetprev>0) #detected of all ages
        }else{
          if(t>=mlen){#(i.e. when the time step is mlen or later)
                                                            #numdetprev<-apply(numdetPcell[,(t-mlen):(t-1),r,1:pers],MARGIN=c(1),sum);sum(numdetprev>0)
            numdetprev<-rowSums(numdetPcell[,(t-mlen):(t-1),r,1:pers]);#sum(numdetprev>0)
          }
        }
        # thus a prob patrol vector is created for each time step and replicate (vector of length 'ncells')
        # now use the resultant vector to assign patrols to cells
        # first convert the vector counts to probabilities that sum to 1
        probpat<-numdetprev/sum(numdetprev);
        probpat[is.na(probpat)]<-0.00;sum(probpat) # confirm it sums to 1
        #now to make sure there are enough positive probabilities for the next sample statement:
        probpat[which(probpat==0)]<-0.00000001
        if(constrained.pat==TRUE){
          probpat<-probpat*dist.camp.df$prob #MULTIPLY probabilities together
        }else{probpat=probpat}
        #now the below samples cells for patrols according to this probability vector (see example just below if statement)
        patrolled<-sample(c(1:ncells),size=numpat.actual,prob=c(probpat),replace=FALSE);patrolled
      }
    }
    #---------------------------------------------
    pat<-list()
    #Now the patrolled cells above represent the patrol base cells, but we want to also include the cells around them

    # library(spdep)
    # nb=poly2nb(gr) #this creates a direct QUEENS neighbourhood matrix, or a list of vectors with each vector i
    left.adj<-numeric()
    av.adj<-list()
    adj.actual<-list()
    high=1.5
    #ndicating the neighbours of each cell. QUEENS includes cells that only touch at a corner
    #so if we take:
    for(p in 1:length(patrolled)){
```

```
centpat<-patrolled[p]
try( #sometimes the loop below returns an error when the adjacent cell selection for a particular
patrol base fails
  #down the line. This happens very rarely (1%). The try statement just means that it skips to
the next step and
  #that single patrol basically does not happen. This will have only a very minor effect (one
missed patrol out of 100)
  #and also happens at the same rate across all scenarios, so not an issue in terms of model
effects
  #If necessary, can modify later to still have that patrol, but only sampling random cells (or
similar)
  for(i in 1:10){
   if(i==1){left.adj[i]<-sizepat-1; av.adj[[i]]<-nb[[centpat]]; av<-length(av.adj[[i]])
   }else{
    if(i==2){
     left.adj[i]<-left.adj[i-1]-length(adj.actual[[i-1]])
     #here we determine which adjacent cells are available and as yet unpatrolled:
     b<-unique(unlist(nb[adj.actual[[i-1]]]));
     av.adj[[i]]<-b[-which(b==centpat)];av<-length(av.adj[[i]])#centpat different
    }else{
     left.adj[i]<-left.adj[i-1]-length(adj.actual[[i-1]])
     b<-unique(unlist(nb[adj.actual[[i-1]]]));
     av.adj[[i]]<-b[-which(b%in%c(unlist(adj.actual[c(1:(i-1))])))];av<-length(av.adj[[i]])
    }
   }
   if(left.adj[[i]]<1){pat[[p]]<-c(centpat,unlist(adj.actual[c(1:(i-1))]));break}
    #Now we have code for deciding whether to select all available adjacent cells, or only a
portion of them
   #this is based on how many cells are left to patrol (left from sizepat). If the number of patrols
left is less
   #than half those available in this adjacent ring, then select all the ones left from this ring
   #if the amount left is more than 1.5 x those available, then select all the adjacent cells in this
ring
   #if the amount left is somewhere in between, then select a certain proportion from this ring
(X)
   if(left.adj[i]<=low*av){adj.actual[[i]]=sample(av.adj[[i]],left.adj[i])}
   if(left.adj[i]>low*av&left.adj[i]<=high*av){
     #in this category, sometimes the number sampled is more than that available, need to
correct:
    if(length(av.adj[[i]])>=round(x*left.adj[i],0)){adj.actual[[i]]=sample(av.adj[[i]],round(x*left.adj[i
],0))
    }else{adj.actual[[i]]=av.adj[[i]]}
   }
   if(left.adj[i]>high*av){adj.actual[[i]]=av.adj[[i]]}
  }
 )
}
pat
cheese<-numeric()
cheese[r]<-sum(unlist(lapply(pat,is.null)))
patrolled<-unlist(pat)
# code to get a vector of number of patrols in each cell of the park  (applies to all patrol scenarios)
patrols[,t,r]<-rep(0,ncells);patrols[,t,r][patrolled]<-1

for(a in 1:pers){
  #this is the function that determines the detection probability from age of carcass (see top of
code)
 dpP=dp.v.age[a]

 if(t==1){
   # now run the detections of all age classes in timestep 1
   df<-numavpcell[,t,r,a][patrolled];sum(df)
```

```
        #NOW SPEED UP CODE by only running the binomial function on cells that are non-zero!
        if(sum(df)==0){ #if there are no carcasses for that age in the patrolled cells at that time step, then...
            numdetPcell[,t,r,a]<-rep(0,ncells) # there obviously are no detections for that age and timestep...

        }else{#************

         #df[20]<-3;df[15]<-1
         df2<-df[df>0]
         #numdetPcell[names(df2),1,1,1]
         # now the number detected in each patrolled cell is a binomial RV with:
         # n = 1 , 1 sample from the binomial distribution is taken (one patrol_
         # size = the number of trials (i.e. the true number of carcasses available for detection)
         # prob = the detection probability for that carcass type

         temp<-unlist(lapply(df2,function(x){ rbinom(n=1, # one sample from the binomial dis
                                              size=x, # size = num trials (num carcasses avail)
                                              prob=dpP)}));temp# dpP = detection probability for poached
                                         numdetPcell[,t,r,a]<-rep(0,ncells);numdetPcell[,t,r,a][names(temp)]<-temp;sum(numdetPcell[,t,r,a])
         #apply(numdetPcell[,1,1,5:15],2,sum)

        }#***************

       }else{if(t>1&a==1){

        #now for every time, step, this is the number of fresh (<1 month, a=1) carcasses detected
        df<-numavpcell[,t,r,a][patrolled];sum(df)
        if(sum(df)==0){ #if there are no carcasses for that age in the patrolled cells at that time step, then...
            numdetPcell[,t,r,a]<-rep(0,ncells) # there obviously are no detections for that age and timestep...
        }else{
         df2<-df[df>0]
         temp<-unlist(lapply(df2,function(x){ rbinom(n=1,size=x,prob=dpP)}));temp
                                         numdetPcell[,t,r,a]<-rep(0,ncells);numdetPcell[,t,r,a][names(temp)]<-temp;sum(numdetPcell[,t,r,a])
         #apply(numdetPcell[,1,1,5:15],2,sum)
        }
       }else{if(t>1&a>1){
        #t=2;a=3
        df<-numavpcell[,t,r,a][patrolled];sum(df)
        if(sum(df)==0){ #if there are no carcasses for that age in the patrolled cells at that time step, then...
            numdetPcell[,t,r,a]<-rep(0,ncells) # there obviously are no detections for that age and timestep...
        }else{
         df2<-df[df>0]
         temp<-unlist(lapply(df2,function(x){ rbinom(n=1,size=x,prob=dpP)}));temp
                                         numdetPcell[,t,r,a]<-rep(0,ncells);numdetPcell[,t,r,a][names(temp)]<-temp;sum(numdetPcell[,t,r,a])
         #apply(numdetPcell[,1,1,5:15],2,sum)
        }
       }
       }
       }
      }
    }
  }
  end_time <- Sys.time() # record the time at which the code starts running (to see time length)
  time_to_run<-end_time-start_time # record the time at which the code starts running (to see time length)
```

```
  print(time_to_run)
  print(tsteps.rand)

  ######CALCULATE AND STORE KEY OUTPUTS-------------------------------------------------------------
-----------------------

  ###COMMUNITY INTELLIGENCE:
   #now simply add the fresh carcasses detected through intelligence to the array of detected
carcasses:

  if(hc.extra==T){ #only run this for the situation where a=1
    for(r in 1:nreps){
      for(t in 1:timesteps){
        numdetPcell[,t,r,1]<-numdetPcell[,t,r,1]+numdetPcell.hc[,t,r]
      }
    }
  }
  #This is the number of carcasses of each age available and detected for each tstep and rep.
  numavpcell[,-c(1:burn),,]
  numdetPcell[,-c(1:burn),,]
  av.det.ages<-list(numavpcell,numdetPcell)

  #simplify to get the number for each age class, each time step, for available
   fresh<-apply(av.det.ages[[1]][,,,1],MARGIN=c(2,3),sum);fresh<-apply(fresh,c(1,2),sum);fresh.av<-
fresh;fresh.av
                                  recent<-apply(av.det.ages[[1]][,,,2:6],MARGIN=c(2,3,4),sum);recent<-
apply(recent,c(1,2),sum);recent.av<-recent;recent.av
      old<-apply(av.det.ages[[1]][,,,7:24],MARGIN=c(2,3,4),sum);old<-apply(old,c(1,2),sum);old.av<-
old;old.av
                                  v.old<-apply(av.det.ages[[1]][,,,25:48],MARGIN=c(2,3,4),sum);v.old<-
apply(v.old,c(1,2),sum);v.old.av<-v.old;v.old.av

  ages.av<-list(fresh.av,recent.av,old.av,v.old.av);names(ages.av)<-c("fresh","recent","old","v.old")

  #now for detected
  fresh<-apply(av.det.ages[[2]][,,,1],MARGIN=c(2,3),sum);fresh<-apply(fresh,c(1,2),sum);fresh.det<-
fresh;fresh.det
                                  recent<-apply(av.det.ages[[2]][,,,2:6],MARGIN=c(2,3,4),sum);recent<-
apply(recent,c(1,2),sum);recent.det<-recent;recent.det
     old<-apply(av.det.ages[[2]][,,,7:24],MARGIN=c(2,3,4),sum);old<-apply(old,c(1,2),sum);old.det<-
old;old.det
                                  v.old<-apply(av.det.ages[[2]][,,,25:48],MARGIN=c(2,3,4),sum);v.old<-
apply(v.old,c(1,2),sum);v.old.det<-v.old;v.old.det

                                  ages.det<-list(fresh.det,recent.det,old.det,v.old.det);names(ages.av)<-
c("fresh","recent","old","v.old")
  av.det.ages.2<-list(ages.av,ages.det)

  #now sum across all ages to get total number available and detected
  numavpcell.all<-apply(numavpcell,MARGIN=c(1,2,3),sum);
  numdetPcell.all<-apply(numdetPcell,MARGIN=c(1,2,3),sum)
  #a<-numavpcell.all[,50,1]; sum(a); sum(numavpcell[,50,1,1:48]) # Check these two match

  # now create a list with all the outputs
  results.full<-list(numpcell,numavpcell.all,numdetPcell.all,patrols,numdetPcell.hc)
  names(results.full)<-c('nump','numavp.all','numdetP.all','patrols',"det.hc")
  results.full<-lapply(results.full,function(x){x[,-c(1:burn),]})
  end_time <- Sys.time() # record the time at which the code starts running (to see time length)
  time_to_run<-end_time-start_time # record the time at which the code starts running (to see time
length)
  print(time_to_run)

  return(list(results.full,av.det.ages.2,
```

```
        rp.m)) #rp.m is the actual poaching rate simulated for each tstep and rep (whole park)
}
```

# 2. Appendix 2: Interview guide used for park rangers (Chapter 5)

*General duties and job satisfaction*

1. How long have you been working as a ranger in Zimbabwe and how long have you been working at this site?

2. Could you tell me about your duties as a ranger, what are the different activities you are involved in?
   - *Prompt: patrols, general monitoring, maintenance, manning stations, anti-poaching, wood collection, slashing?*

3. What do you like about being a ranger? What are the positives?
   - *Prompt: What parts of the job do you enjoy the most?*

4. What do you not like about being a ranger? What are the main challenges and difficulties you face as a ranger?
   - *Prompt: Have you ever faced a life-threatening situation as a ranger?*
   - *Prompt: What is it like living far from family?*
   - *Prompt: Do you feel you have the equipment you need to do your job?*

*Patrols*

5. Could you tell me a bit more about patrols? What is the purpose of patrols? What are the different kinds of patrols you are involved in?
   - *Prompt: Strategic and intelligence led anti-poaching, daily local patrols, extended patrols to widen coverage and general monitoring.*
   - *Prompt: How much time do you spend on patrol versus other activities and duties?*

6. How frequently do you patrol? How much time do you spend on each type of patrol?

7. Could you tell me about a recent patrol (NB to get a tangible story).
   - purpose/type, brief details, method of deployment
   - length, number rangers, equipment
   - area covered, patrol bases or sub-stations
   - info recorded and how, communication with camp method and frequency

*Involvement in and experiences of MIKE data collection*

8. What kind of information do you collect on patrol?

9. Have you heard of the MIKE programme – MIKE? Do you know what it stands for? [Assure them it is ok if you don't].

10. Does your job as a ranger involve finding and reporting on elephant carcasses?
    - *Prompt: Have you yourself ever been on a patrol during which a carcass was detected?*
    - *Prompt: How many times have you been on a patrol that found an elephant carcass? What proportion of all patrols?*

11. How do you manage to fit in monitoring of elephant carcasses with your other duties?
    - *Prompt: Would you say that monitoring carcasses is a big or small part of your job?*
    - *Prompt: Is collecting information on elephant carcasses a burden or does it support your other work?*

12. Could you describe the last time you found an elephant carcass on patrol?
    - *What type of patrol were you on? General or intelligence-led?*
    - *How did you detect the carcass?*
    - *What did you do once you found the carcass? What information did you record?*
    - *How did you determine cause of death?*
    - *Did you report the details? How?*

13. How do you normally find elephant carcasses?
    - *Prompt: Do you come across carcasses randomly on routine patrols?*
    - *Prompt: Do you find carcasses by responding to intelligence/information on poachers (e.g. gunshots)?*

14. Could you share some of your general thoughts on and experiences with finding and collecting information on elephant carcasses?
    - *Prompt: Compared to your other duties, do you enjoy this?*
    - *Prompt: Would you say that monitoring elephant carcasses is easy or difficult? Why?*

*Recording, reporting and processing MIKE Data*

15. How do you record the information on an elephant carcass when you find one?
    - *Prompt: Do you use paper carcass forms (MIKE) or enter information into mobile devices? Which do you prefer?*
    - *Prompt: Do you use SMART and the new cybertrackers? If so, how do you feel about this system? Are there any challenges?*

16. How do you report the elephant carcass information to management/supervisors?

17. Who enters and processing the data on wildlife observations (elephant carcasses) at the station? Are you involved? Do you know any rangers who are involved in this?

18. How would you describe your relationship with your supervisors [Wildlife Officer/Area Manager]?
    - *Do you enjoy working with them? Are there some challenges? Good leadership?*

*Awareness of purpose of MIKE data collection and perceptions of value*

19. What do you think is the purpose of monitoring elephant carcasses at this site?
    - *Prompt: Why do you think you are required to collect data on elephant carcasses?*

20. Do you know what happens to the elephant carcass data once you report it? What is the information used for?
    - *Prompt: Do you know how the data is used by management?*
    - *Prompt: Does management report the data to a higher level? Could you give details*

21. Do you personally think it is important to collect this information? Why?

22. Do you get feedback (e.g. monthly, yearly) on summaries of all the elephant carcass data that is collected by rangers?
    - *Prompt: If so, how does the feedback make you feel?*
    - *Prompt: If not, would you like to get feedback? Why?*

23. Do you think the information on elephant carcasses that is collected by rangers helps with elephant protection and anti-poaching?
    - *Prompt: If so, in what way? Could you share some examples of how it helps?*

*Concluding questions*

24. We are now coming to the end of the interview. Could I ask you to summarise your thoughts and feelings about patrols and monitoring elephant carcasses through MIKE?

25. What advice would you give in order to improve the MIKE programme?

26. Is there anything else you would like to add or feel you didn't get the chance to mention?

# 3. Appendix 3: Interview guide used for park managers (Chapter 6)

*<u>Opening general questions</u>*

1. How long have you been at this site? Could you tell me a bit about what your job as an area manager (wildlife officer, etc.) involves? What are your various duties and responsibilities?

2. My research involves elephant poaching. What are some of the main strategies used to reduce elephant poaching at this site?

3. How do you develop these strategies?

4. What sources of information do you use to inform these strategies?

*<u>General involvement in MIKE and purpose</u>*

5. Am I right to assume you have you heard about the MIKE programme? How did you first hear about or become involved in MIKE?

6. Are you personally involved in MIKE now? If so, in what ways does your work involve MIKE? What are your responsibilities in connection with MIKE?

   - *Prompt: I understand you have many duties, how does MIKE fit in alongside these?*
   - *Prompt: Is MIKE a small or big part of your job?*

7. What, in your opinion, is the purpose of MIKE monitoring at this site?

   - *Prompt: Why are the data collected and reported? CITES or local?*
   - *Prompt: What is your motivation for collecting and reporting data?*

*<u>General collection and reporting of data</u>*

8. Could you share any general information on how MIKE data on elephant carcasses are collected at this site?

9. What happens to the elephant carcass data once it has been collected at this site?

   - *Prompt: Who is the data reported to and why? [management/CITES]*
   - *Prompt: How are the data reported?*
   - *Prompt: Are you aware of how the MIKE data are used once it has been reported?*

10. Could you share an example or story from your own work and experience this year about reporting of MIKE data from this site?

    - *Prompt: Is there a report example you could share with me?*

11. Who is responsible for analysing and interpreting MIKE data from this site and reporting results?

- *Prompt: Are you personally involved in analysis and interpretation?*
- *Prompt: How is the ecologist involved? Should they be doing the analysis?*
- *Prompt: Do you expect feedback from ecologist? If so, what kind and how does it help?*

12. Is SMART used at this site? If so, could you share a bit more about how it works?

    - *Prompt: Example of how you yourself have used SMART?*
    - *Prompt: How is SMART integrated with MIKE data?*
    - *Prompt: Are there any challenges with SMART – is it difficult to use? Computer, training?*
    - *Prompt: Do you use it for analysis?*
    - *Prompt: What are your general opinions of SMART?*

*Use of elephant mortality data for local elephant management and anti-poaching*

13. I understand it is important to report MIKE data. However, do you as a manager find the information useful?

14. How do you make use of MIKE data at this site? Is it for local elephant management and anti-poaching? If so, in what ways?

    - *Prompt: Are MIKE data used to:*
        a. *Measure how anti-poaching is performing, and evaluate/change strategies?*
        b. *Identify poaching hotspots and direct patrol locations, routes and strategies?*

15. Could you share an example or story from your own work and experience this year about using MIKE data for management at this site?

16. What are some of the main challenges that make it difficult to use MIKE data for local management?

    - *Prompt: Is there adequate human capacity and resources to interpret and use data?*
    - *Prompt: Is the data format hard to use, are there concerns about data quality?*

17. Overall, would you say that MIKE makes a small or large contribution to elephant management and anti-poaching at this site?

*Implementation challenges*

18. What are the main challenges to implement and carry our MIKE monitoring effectively at this site?

    - *Prompt: Are general resources (equipment, infrastructure, communications, vehicles) an issue?*
    *Prompt: Is there adequate human capacity, training and expertise?*

19. How do rangers in practice manage to combine monitoring with their other duties and responsibilities, like anti-poaching?

    - *Prompt: Do monitoring and law enforcement complement each other or is there a conflict?*

*Concluding questions*

20. We are now coming to the end of the interview. Could I ask you to summarise your general thoughts and feelings about the MIKE programme?

    – *Prompt: Do you, as a manager/WO/SR see MIKE monitoring as valuable to your work? Why?*

21. We have discussed many aspects and issues, thank you for that, this has been very useful. In the end, what ADVICE would you give to improve matters?

22. Is there anything else you would like to add or feel you didn't get the chance to mention?

# 4. Appendix 4: Interview guide used for national-level respondents (Chapter 6)

*Mainly senior staff at the Zimbabwe Parks and Wildlife Management Authority

*<u>Opening questions</u>*

1. When did you first hear about MIKE monitoring in Zimbabwe and could you tell me a bit about how your work involves MIKE now? Could you share some of your general thoughts and feelings about the programme?

2. What would you say are the main purpose and goals of the MIKE programme in Zimbabwe?
   - *SP: Is there more of an emphasis on (a) international reporting to CITES, or (b) supporting local elephant management and conservation?*

3. Would you say that the MIKE programme in Zimbabwe is externally or locally driven? Could you comment on the level of *local* buy in to the MIIKE programme in Zimbabwe?

*<u>Overall research question 1: Contribution of MIKE data from the Zambezi Valley to local elephant conservation and management.</u>*

4. Could you share any information on what happens to MIKE data from Chewore and/or Mana Pools once they have been collected? How are the data used?
   - *SP: Could you share any information on whether or not MIKE data are used at the local protected area level, i.e., in Chewore and Mana Pools?*
   - *SP: Are the data sent to national headquarters for international reporting to CITES?*

5. In general, would you say that MIKE monitoring and data has or has not contributed to local elephant conservation and management in the Zambezi Valley?

   - *By 'elephant conservation and management' I am referring to any activities and strategies carried out by management staff, rangers and other stakeholders to protect elephants, reduce poaching and raise awareness. Activities may include anti-poaching patrols, general law enforcement, community informant networks, judicial reforms, conservation education and awareness raising.*
   - *SP: Would you say that MIKE data have helped tackle elephant poaching in the ZV?*
   - *SP: Are MIKE data discussed or used at workshops or in protected area or elephant management plans?*

6. Could you share any examples of ways in which MIKE data have been used to support or guide elephant conservation and management in the Zambezi Valley?
   - *SP: Are MIKE data integrated into local management decision-making processes?*
   - *SP: Are MIKE data used by area mangers/ranger to change/improve their anti-poaching strategies?*
   - *SP: Are MIKE data used to measure the effectiveness of management actions in reducing poaching?*
   - *SP: Are MIKE data used in any way for awareness raising or education around elephant poaching?*

7. Could you share examples or ways in which elephant management and anti-poaching in the Zambezi Valley DO NOT depend on or use MIKE data?

8. What would you say are some of the reasons why MIKE data may not be used to support elephant management and conservation in the Zambezi Valley?
   - *SP: What are some of the main challenges that make it difficult to use MIKE data?*
   - *SP: Would you say that there is adequate human capacity, technical expertise and other resources to use and interpret MIKE data for evaluating management?*
   - *SP: Does the quality of the data limit its usefulness for management?*

9. Could you tell me a bit about the use of the SMART in the Zambezi Valley? How does SMART work? How does SMART affect the use of MIKE data by management?

10. What other information on elephant population status and threats in the Zambezi Valley are used to inform elephant management and conservation?

11. Are you aware of the EU-funded CITES MIKES project being implemented in the Mana Pools/Chewore/Sapi World Heritage site? If so, what is your perception of how effective the project has been in terms of increasing capacity for (a) general MIKE monitoring, and (b) anti-poaching activities?

*Research question 2: To what extent do current MIKE data represent true poaching levels and trends and what factors affect this?*

12. In general, would you say that MIKE data provide an accurate or inaccurate measure of the true level of elephant poaching in Chewore Safari Area and Mana Pools National Park?
    - *SP: What makes you think so? Do you have any evidence to suggest that the data are accurate/inaccurate?*

13. In general, would you say that MIKE data provide an accurate or inaccurate measure of changes in true poaching levels over time, i.e., seasonally or from year to year?
    - *SP: is MIKE data able to pick up changes in actual poaching levels*

14. What would you say are the factors that affect the quality and accuracy of MIKE data from Chewore and Mana Pools?
    - SP: Is there adequate effort and coverage by patrols?
    - SP: Are general resources and (equipment, infrastructure, communications) an issue?
    - SP: Is there adequate human capacity and training?
    - SP: Would you say there may occasionally be mis- or under-reporting?

15. How could MIKE monitoring in the Zambezi Valley be made more effective?

16. What are some of the other activities or duties that rangers are responsible for and how does MIKE monitoring fit in alongside these other responsibilities?
    - *SP: How does MIKE monitoring fit in alongside general law enforcement and anti-poaching? Is there conflict or do they complement each other?*

17. Do you have any information on how MIKE data are summarised each year, is there an overall score that is calculated?
    - *SP: In my reading I have come across the PIKE metric and I wondered if you had heard about it?*
    - *SP: Do you think PIKE provides an accurate or inaccurate measure of levels and trends in elephant poaching?*
    - *SP: Could you share your thoughts on possible reasons why the PIKE index might provide unreliable estimates of poaching levels?*
    - *SP: How does the use of natural mortality carcasses in the metric affect its accuracy?*
    - *SP: Would you say that the PIKE index is useful or not useful for informing management?*

END OF INTERVIEW: Is there anything else you would like to add or feel you didn't get the chance to mention? Thank you so much for participating, your insights will help my research greatly.

# 5. Appendix 5: Interview guide for senior staff of the MIKE programme (Chapter 6)

<u>*Opening questions*</u>

I would like to start with some questions about your work, and your involvement in MIKE:

1. Could you tell me a bit about your current work?
2. When did you first become involved in the MIKE programme?
3. In what ways does your work involve MIKE now?

<u>*General MIKE questions:*</u>

4. What, would you say, are the main aims or goals of the MIKE programme?
5. What, would you say, are the main successes of the programme as a whole to date?
6. What, would you say, are the main challenges the programme has faced?

<u>*MIKE implementation locally*</u>

7. My understanding is that MIKE aims to contribute both to international policy through forums like the CITES CoPs, as well as to local elephant management. How would you say MIKE has performed in each of these two areas?
- *Prompt: Has MIKE performed better in one of these areas than the other? Why?*
- *Prompt: Does your particular role involve more work with the international policy aim, or with the local management aim?*

8. Could you describe for me your experiences of the relationship between MIKE as a programme and local actors at MIKE sites?
- *Prompt: Could you tell me very generally the role that each party plays in this relationship?*

9. What is the vision for how MIKE as a programme contributes to local elephant management at MIKE sites?
- *Prompt: How is MIKE designed to achieve this vision?*
- *Prompt: What is the theory of change for how MIKE contributed to local elephant management?*

10. At the local level, there is on the one hand the monitoring elephant poaching levels, and on the other hand there is the management of elephant poaching. What is the role of MIKE for each of these?

11. In what <u>particular</u> ways is MIKE able to help local protected area managers in their work to conserve elephants?
- *Prompt: Could you provide some tangible examples of how MIKE data might be used locally?*

12. What would you say are some of the challenges you have seen in terms of MIKE contributing to local elephant management?

13. One of the stated goals of MIKE is to build local capacity for long-term elephant management in range states. What would you say is the goal of this capacity building, and what does it look like in practice?

14. In your experience, what are some of the barriers you have seen in terms of implementing MIKE successfully at the local level?

*The Zimbabwe Case Study*

Give a brief overview of the work I have done in the Zambezi Valley MIKE site in Zimbabwe, explaining I have spoken to rangers, park managers, and with national wildlife staff.

15. Some of the managers and national level staff in Zimbabwe saw MIKE mainly as a reporting requirement to CITES but did not always take ownership of MIKE and see its value for local elephant management:
- *Prompt: Why do you think local actors see MIKE mainly as a reporting requirement?*
- *Prompt: In what way does the MIKE programme seek to promote greater local ownership of MIKE in terms of promoting greater integration of MIKE with local management?*

16. When I spoke to park managers, I noticed there was not always clarity about the role that MIKE should play, and the role that the managers themselves should play in terms of adaptive management of elephants using elephant mortality data.
- *Prompt: Could you comment on what you see as the role of MIKE as a programme, and the role of local managers, in terms of the monitoring and management of elephant poaching?*

17. Local actors in Zimbabwe also complained that they did not receive feedback from MIKE on their data, and sometimes even expected MIKE staff to analyse patterns in local data and then give feedback?
- *Prompt: Can you comment on this expectation? Would you say MIKE should provide such feedback?*
-

*The way forward*

18. In your opinion, what do you think are some of the ways MIKE could be improved to better contribute to local elephant management?

Thank you so much for your time. Is there anything else you would like to comment on or mention?