Innovation adoption theory in wildlife management and conservation: initial insights from a case study of machine-vision and Cape buffalo management in South Africa

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ABSTRACT

The rapid advancements in technology, particularly of artificial intelligence, provide many new opportunities for conservation management. However, they also present many challenges as the novelty of these technologies in conservation makes the discipline susceptible to hype, poor planning, and 'techno-fixes', which ultimately end up wasting time and resources. In this paper, I deploy innovation adoption theory to investigate a potential technology-based machine vision solution to a clear problem in Cape buffalo management and conservation in South Africa. Using the lens of innovation adoption theory provided valuable insight into the management structure investigated and identified concerns and obstacles that would need to be addressed for successful implementation of the technology-based machine vision solution. Utilising the well-developed theory of innovation adoption to guide the future of technology in conservation provides a promising solution the challenges facing digital conservation, ensuring that future technology implementation in conservation is as effective and efficient as possible.

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ABBREVIATIONS

SAWC: Southern African Wildlife College

APNR: Associated Private Nature Reserves

KNP: Kruger National Park

GKNP: Greater Kruger National Park

TPNR: Timbavati Private Nature Reserve

WWF: World Wildlife Fund

VGG: Visual Geometry Group

VIA: VGG Image Annotator

PH: Professional Hunter/ing

IT: Information Technology

MVM: Machine Vision Model

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1 DECLARATION OF INTELLECTUAL CONTRIBUTION

For one aspect of my dissertation research, I collaborated closely with Dr. Carlos Arteta, a post-doctoral researcher based at the Physical Geometry Group of the University of Oxford's Department of Engineering Science. Arteta is an expert in machine vision technology and he assisted with my research by developing the machine vision application discussed throughout the paper. I claim no intellectual ownership over nor intellectual contribution to the machine vision application itself or its design. However, as discussed later, I collected, annotated, and curated the dataset used by Arteta for training the machine vision model and assessed the application myself on a separate dataset. In my methods section when describing the design and engineering of the application and in my results when reporting on the model's performance I will refer to a brief written exclusively by Arteta that is included in the appendices of my dissertation.

2 INTRODUCTION

As planet Earth delves further into the Anthropocene (Lewis & Maslin 2015), the need for best practice in natural resource and ecosystem management on the part of its human residents continues to grow (Collen et al. 2009; WWF 2016). Though life and natural systems thrive in the absence of man, with a current human population of over seven billion and a projected expansion of that population to nearly 10 billion by 2050 (United Nations 2015) innovation in the methods used to inform and govern society's relationship with nature is more important now than ever before. Improved practice in wildlife management and conservation is of particular concern as the continued degradation, fragmentation, and downgrading of Earth's life systems is an inevitability in the coming decades (Estes et al. 2011; Malhi et al. 2016).

Recent advancements in data capture and analysis technologies, particularly through the varying forms of artificial intelligence, provide many opportunities for improvements in conservation and wildlife management decision making that have yet to be implemented. The onset of this new technology however does present challenges for conservation (Arts et al. 2015; Joppa 2015) and tools for assessing a potential technology solution are necessary. Machine vision technology presents a valuable opportunity for the management and conservation of Cape buffalo (*Syncerus caffer caffer*), as it would enable rapid demographic level analysis of buffalo populations. The aim of this research is to investigate the potential applicability of innovation adoption theory (Gallivan 2001) to wildlife and environmental conservation contexts using machine vision and Cape buffalo management in South Africa as a case study. While more developed than many other African countries (Central Intelligence Agency 2017), South Africa remains one of the leading strongholds for African wildlife (Grenyer et al. 2006). It holds the world's largest population of black rhino (*Diceros bicornis*) and white rhino (*Ceratotherium simum*)(Rademeyer 2016; Emslie et al. 2013) and has important areas for many of the other rare African mammals (Grenyer et al. 2006). While South Africa has designated many important national parks and protected areas, the privatisation of wildlife resources model (either through ownership or usage rights) adopted by many southern African countries in the late 20th century (Muir-Leresche & Nelson 2000; Naidoo et al. 2011) has been key to the country's conservation success (Rubino & Pienaar 2017). However, with growing pressure from threats including habitat loss, land conversion, and poaching, communities, landowners, and reserves will need better tools to tackle the growing challenges faced as pressure on natural systems continues to grow.

2.1 Innovation Adoption Theory

Innovation adoption theory, how innovations are developed, adopted, and assimilated into the day to day process of organisations or by individuals within an organisation (Daft 1978; Lei 2016), is surrounded by an extensive body of well developed literature (Rogers 1962; Moch & Morse 1977; Tornatzky & Klein 1982; Leonard-Barton & Deschamps 1988; Davis et al. 1989; Cooper & Zmud 1990; Prescott & Conger 1995; Taylor & Todd 1995; Karahanna et al. 1999; Gallivan 2001). From this literature, numerous theories and frameworks for explaining innovation adoption into organisations and the diffusion of innovation across them in differing ways and from various angles have emerged (Daft 1978; Cooper & Zmud 1990; Gallivan 2001; Courchamp et al. 2006). This literature focuses almost entirely on information technology (IT) based organisations and innovations and has yet to branch into other disciplines. However, the research and frameworks developed for IT organisations present many opportunities for studying innovation in wildlife management and conservation.

Gallivan (2001) presents a theoretical framework (Figure 1) that combines theory on individual innovation adoption with theory on organisational innovation implementation to create a hybrid framework that more robustly captures the complexity of interplay between managers, selected strategies, and other inherent factors of organisations. The framework, shown in Figure 1, dissects the innovation adoption process into three main parts: the primary authority decision, secondary adoption and assimilation, and the organisational consequences. The primary authority section describes the top management level decision to adopt an innovation or not, and is relatively straightforward and well understood (Chengalur-Smith & Duchessi 1999). The secondary adoption and assimilation section contains the majority of the complexity of the framework and is further broken down into three constructs: managerial intervention, subjective norms, and facilitating conditions. Together these three constructs (shown in green in Figure 1) dictate the occurrence of the secondary adoption process and assimilation stage of innovation adoption, and are the focus of this study. The last section is organisational consequences, which describes the result of innovation adoption on the organisation adopting it.

Managerial interventions describe not just the decisions made by managers as to whether or not to adopt an innovation, but also the action they take to ensure the adoption process is a success (e.g. training, resources, support, etc.). Subjective norms describe the individual actors' beliefs about the innovation, including its role within their responsibilities and whether or not the innovation should be adopted or abandoned. As stated by Gallivan (2001, p.61), facilitating conditions 'is a broad category that captures other factors that can make implementation more- or less-likely to occur'. These can include attributes of the innovation itself, the organisation, or of individuals and can also include aspects of the environment in which a particular innovation would operate. The influx of advanced technology into conservation and environmental science presents many new opportunities, but they come with many challenges as well (Arts et al. 2015; Joppa 2015). As many technologies are novel to conservation problems, projects aiming to utilise advanced technology for a given problem are susceptible to poor planning and 'techno-fixes' which do not work as intended and end up wasting time and resources. Applying the principles of innovation adoption theory presented in Gallivan's (2001) framework to conservation and wildlife management presents one potential avenue for critically assessing a technology's applicability to a conservation problem and its likelihood of successfully assimilating into the system. Conservation is already extremely resource limited (Arts et al. 2015) and as more opportunities for technology in conservation become apparent, practitioners will need tools to assess a potential solution to a given scenario before committing full resources to the development and implementation of that solution. Innovation adoption theory adapted from IT management to conservation and wildlife management may provide such a tool.

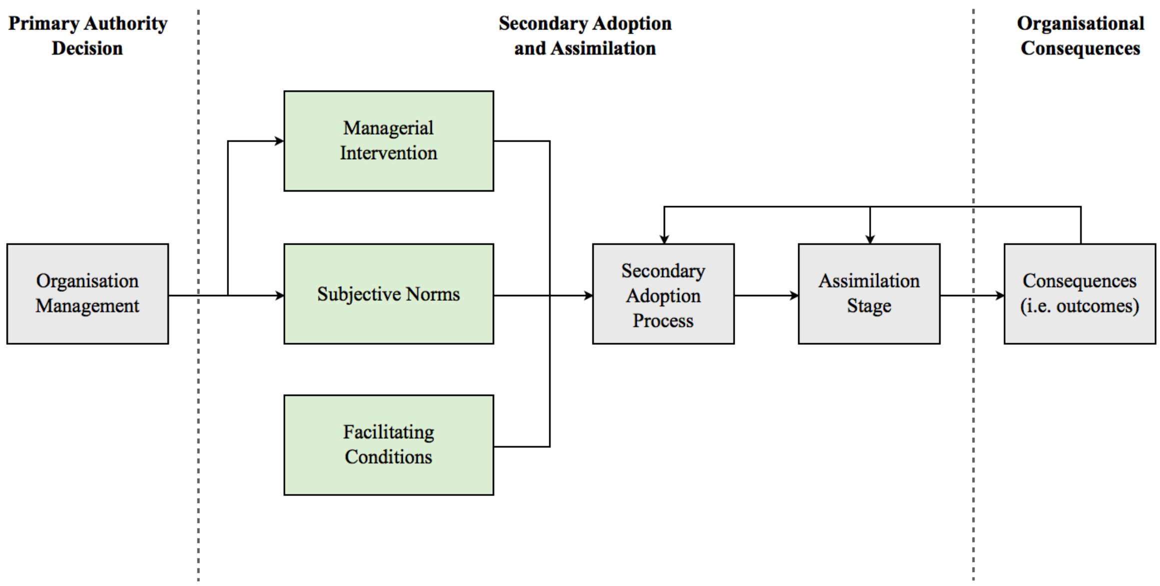

Figure 1: Innovation adoption theory framework adapted from Gallivan (2001). The aspects of this framework targeted primarily in this research are shaded in green.

2.2 Study Site

This research was conducted in collaboration with the Southern African Wildlife College (SAWC) within the property of the Associated Private Nature Reserves (APNR) along the western border of the Kruger National Park (KNP) (Figure 1), primarily within the property managed by SAWC (S 24.541388˚ E 31.334225˚), which is owned by the World Wildlife Fund (WWF), and a private reserve to the north called Timbavati Private Nature Reserve (TPNR). KNP and the neighbouring private APNR reserves that lie on the western border of the park collectively form what is known as the Greater Kruger National Park (GKNP). This body is a representation of the joint conservation initiative established between the KNP and the APNR set up in 1993 (Venter et al. 2008; Timbavati Private Nature Reserve n.d.). Mammal species found commonly in the area include Cape buffalo (*Syncerus caffer caffer*), elephant (*Loxodonta africana*), black and white rhino, blue wildebeest (Connochaetes taurinus), zebra (*Equus quagga*), giraffe (*Giraffa camelopardalis*), impala (*Aepyceros melampus*), warthog (*Phacochoerus africanus*), lion (*Panthera leo*), cheetah (*Acinonyx jubatus*), leopard (*Panthera pardus*), wild dog (*Lycaon pictus*), and spotted hyaena (*Crocuta crocuta*). The area receives on average 570mm of rainfall each year and the land is a proclaimed conservation area.

This site was chosen due to SAWC's interest in the potential applications of artificial intelligence in wildlife management, particularly for the management of Cape buffalo, and because of their involvement with the neighbouring reserves and its proximity to the private wildlife management and conservation system of the region that this research focused on. This provided access to data and expertise that otherwise would have been limited or unavailable. Additionally, with its proximity to the KNP and the world's largest population of free-ranging rhino (Emslie et al. 2013), the implications of this study potentially extend far beyond its research and private wildlife management value to the conservation of one of the most heavily poached and threatened species globally.

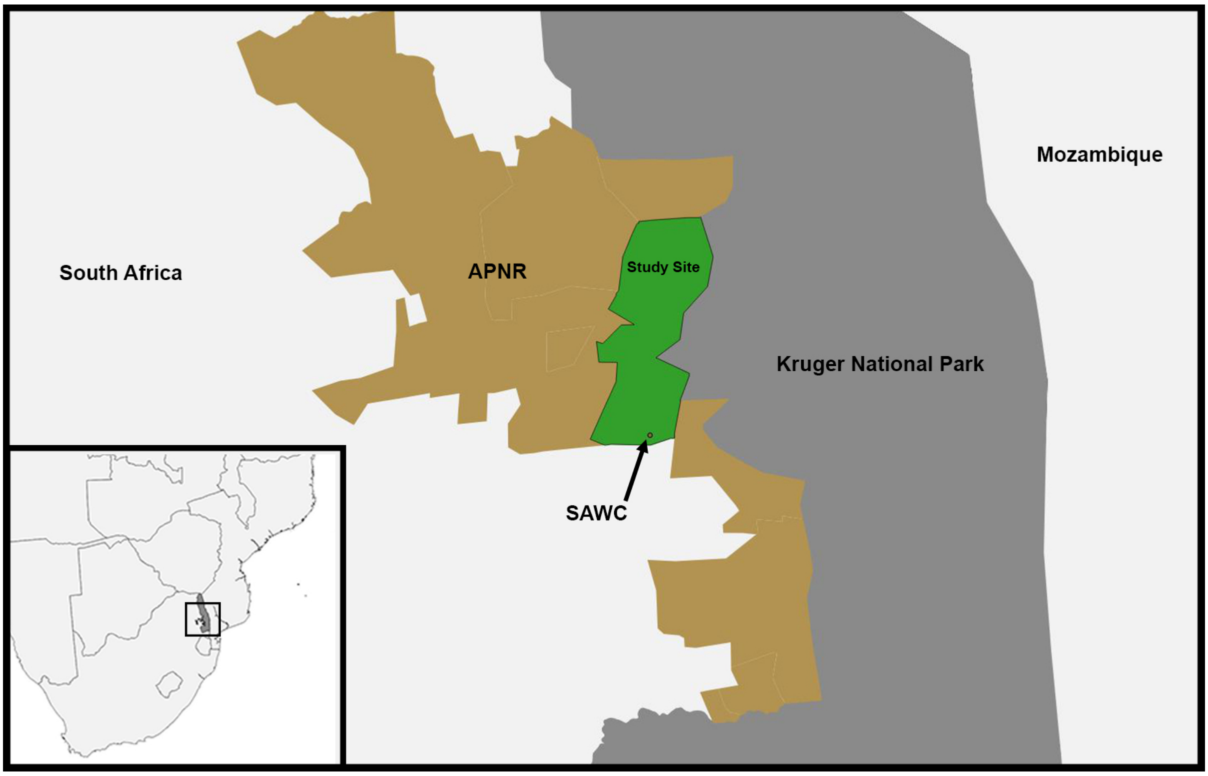

Figure 2: Study site within the APNR, shaded in green and the location of the host organisation SAWC

2.3 Case Study Species – Syncerus caffer caffer

The African buffalo is the largest wild African member of the family Bovidae and historically ranged throughout all of sub-Saharan Africa but is now predominantly found in protected areas. With an estimated global population of 900,000 individuals, the African buffalo is currently listed by the IUCN as 'Least Concern' though some subspecies are decreasing (IUCN SSC Antelope Specialist Group 2008). The African buffalo exists in a variety of different habitats as though they primarily graze, they can also browse on leafy vegetation when such nutrition sources are available. Primary threats to African buffalo include habitat loss and poaching but the species is particularly susceptible to drought and disease, which are responsible for a variety of localised population declines and extinctions, including a substantial decrease in the KNP's population of buffalo from 1994-1995 (IUCN SSC Antelope Specialist Group 2008; Winterbach 1998).

There exist four subspecies of *Syncerus caffer*: the forest buffalo (*S. c. nanus*), the west African savanna buffalo (*S. c. brachyceros*), the central African savanna buffalo (*S. c. aequinoctialis*), and the southern savanna buffalo (*S. c. caffer*) also known as the Cape buffalo and will from here on be referred to as the Cape buffalo (Melletti et al. 2014; IUCN SSC Antelope Specialist Group 2008). The Cape buffalo is the most populous subspecies of the African buffalo and was the subspecies targeted in this research.

2.4 Research Ontogeny

The trophy hunting industry, albeit highly controversial and without a dominant consensus amongst conservationists and researchers concerning its contribution to conservation (Coltman et al. 2003; Hutton & Leader-Williams 2003; Lindsey et al. 2006; Lindsey et al. 2007; Lindsey et al. 2012; Di Minin et al. 2016a; Ripple et al. 2016; Di Minin et al. 2016b; Muposhi et al. 2017; Macdonald et al. 2017), provides a vital stream of finances for the operation of many nature reserves and protected areas throughout southern Africa and is a significant funder of direct and indirect conservation related activities in these areas (Lindsey et al. 2006; Naidoo et al. 2016). Foreign hunters are particularly interested in big game species, including the Cape buffalo due to its size and reputation for being a dangerous species to hunt (Johnson et al. 2010; Palazy et al. 2012). While most landowners, communities, and reserve managers are keen to ensure their buffalo populations are hunted in a sustainable manner, there has been a notable decrease in the average trophy size (i.e. spread of horns in inches from outside edge to outside edge) of buffalo populations in many South African reserves. This is likely due to the artificial selection (via trophy hunting) against the individuals with the largest horns before they have had a chance to breed. Trophy hunting, contrary to natural predation, targets the strongest, largest, and most healthy individuals within a population (Coltman et al. 2003), which results in a state of artificially driven evolution (Allendorf & Hard 2016; Harris et al. 2002). Similar trends have been attributed to the selective pressure of trophy hunting (i.e. hunters targeting individuals with the largest horns) on populations of buffalo in Zimbabwe (Muposhi et al. 2016) and many other popular game species (Thelen 1991; Jachmann et al. 1995; Harris et al. 2002; Coltman et al. 2003). While decisions of which individual to hunt had historically been left to the hunting client, reserve managers and the government have established stricter protocols and guidelines to ensure genetic and ecological sustainability in trophy hunting (Sowry 2017). However, despite the popularity of buffalo as a trophy species, many reserves that practice hunting often lack a detailed understanding of their influence on the genetic and demographic structure of buffalo populations. If a problem is unknown steps cannot be taken to solve it. This lack of understanding stems primarily from insufficient demographic level (e.g. population sex and age ratios) population data as current survey techniques, while increasingly robust, only provide information about population size (i.e. number of individuals)(Pollock & Kendall 1987; Pollock et al. 2002; Winterbach 1998; Thomas et al. 2010). Were demographic level data capture made possible during routine Cape buffalo surveys, managers would be better equipped to ensure that effective off-take regulations and quotas are set to ensure genetic and ecological sustainability in the practice.

The differences in physical characteristics of male and female buffalo and immature and mature buffalo are significant enough to visually distinguish between males and females and between sub-adults and adults (Pienaar 1969; Melletti et al. 2014). Additionally, as the average ear width (from outside tip to outside tip) of adult Cape buffalo is 32 to 33 inches (Robertson, unpublished data) the horn spread of adult buffalo can be estimated visually. However, this skill requires training, experience, and practice to execute well. The advent of new and rapidly improving machine vision technologies (Mishra et al. 2017; Salahat & Qasaimeh 2017; Wilf et al. 2016) provides a potential solution to this specific problem with Cape buffalo and presents many other opportunities for wildlife management and conservation. However there is currently little understanding as to how these state-of-the-art technologies could or should act within the spheres of management that currently exist, which presents some concerns discussed by Arts et al. (2015). By addressing this knowledge gap, wildlife managers and conservationists will be better equipped to find and deploy these technologies for the particular management situation at hand. This situation provides a prime scenario in which to apply the theoretical framework of innovation adoption theory and to test its potential contributions to the future of digital conservation.

2.5 Aims and Objectives

My research aims to identify and discuss the feasibility and applicability of using innovation adoption theory for analysing and assessing potential technology based solutions to management and conservation problems. Additionally, I will assess the feasibility of deploying machine vision technology in Cape buffalo management. I will use this situation of Cape buffalo management and machine vision as a specific case study and will analyse the space using the lens and theoretical framework of innovation adoption theory (Gallivan 2001). Towards this goal, I have divided the research into three key objectives:

1. To test the feasibility of a machine vision model (from here on referred to as the 'MVM') for rapidly analysing the demographics of entire buffalo herds from aerial imagery
2. To assess the social, political, ecological, and economic environment in which the MVM would function to improve the day-to-day management of cape buffalo, with particular emphasis on better decision making in the trophy hunting sector
3. To identify and address the applicability of deploying innovation adoption theory in wildlife management and conservation and the implications it poses for the future of digital conservation

I will use a mixed-methods approach to gain a full understanding of innovation adoption theory's value in the Cape buffalo management of South Africa and of the potential role that machine vision technology could have in this space (Teddlie & Tashakkori 2006). After presenting my findings, I will then discuss their implications for machine vision in Cape buffalo management and address the implications of applying innovation adoption theory to assessing potential technology based solutions to conservation problems. Finally, I will conclude with suggestions on the future of innovation adoption theory in conservation and outline where more research and development may be necessary.

2.6 Beyond the Scope of this Study

The literature provides many cases of evidence and support for private (both individual and community based) conservation practices (Muir-Leresche & Nelson 2000; Rubino & Pienaar 2017; Mbaiwa 2017; Langholz 1996) with some noted limitations and areas to improve (Cousins et al. 2008; Langholz et al. 2000). However, the private model of conservation remains steeped in controversy and critique of the model is expanding. Issues such as inequality in benefit (Spenceley & Goodwin 2007; Pasmans & Hebinck 2017), 'new colonialism' via 'green' land grabs (Holmes 2014), poor strategic planning (Pasquini et al. 2011), and ultimately the subversion of biodiversity conservation by neoliberal capitalism (MacDonald 2010) all underpin the arguments against private nature conservation. Though I recognise some validity of these arguments and while more research is certainly necessary around this topic, such debate is beyond the scope of my research. My research will focus on utilising innovation adoption theory to analyse the management and decision making space within a private nature conservation system and how the system could be improved with advanced technology. My research will not extend to the debate for or against this model, beyond what is necessary to deliver and discuss my findings.

3 LITERATURE REVIEW

3.1 Private Wildlife Management: The Southern African Context

In the late 20th century, following nearly an entire century of failed centralized protectionist legislation over wildlife resources established by colonial regimes, many southern African nations including South Africa began passing over varying degrees of wildlife usage and ownership rights to private landowners and communities (Bond et al. 2004). Despite being protected, wildlife populations were illegally decimated to make way for profitable land uses, primarily agriculture. By passing wildlife rights over to private landowners and communities, governments hoped to reverse the trend of crashing wildlife populations. This decision was grounded in the logic that by delivering wildlife as an exploitable private resource, landowners would take steps of their own accord to maximise and secure the wellbeing of the wildlife populations living on their land (Muir-Leresche & Nelson 2000; Bond et al. 2004). As a result of this policy change there was a massive land use shift from commercial livestock and crop agriculture to game farming and nature reserves (Bond et al. 2004). Some landowners began partnering with neighbours to established larger reserves where all parcels of land were managed as a cohesive whole with each landowner maintaining ownership over his property (Bond et al. 2004; Krug 2001; Timbavati Private Nature Reserve n.d.; Klaserie Private Nature Reserve n.d.). As a result of the changing policy, wildlife numbers increased in much of the region by at least 70%, species diversity increased by 44%, and the net value of land that made the switch from traditional ranching practices doubled (Yaron et al. 1996; Richardson 1998; Barnes et al. 2002; Krug 2001). Under the new legislation, landowners, both individuals and those as part of larger private reserves, could make use of the wildlife resources on their land via a variety of channels.

3.1.1 Consumptive versus Non-consumptive Use

Wildlife use is generally categorised into either consumptive or non-consumptive use. Non-consumptive use generally consists of wildlife viewing and photographic safaris. Consumptive use can further be divided into consumptive tourism, which includes trophy hunting and fishing, and consumptive use, which includes use of meat, skins, and other products from the animal (Yaron et al. 1996; Richardson 1998). The majority of private reserves within South Africa utilise a combination of consumptive and non-consumptive uses, although some may place more emphasis on one strategy over another depending upon their location and the ecological and aesthetic characteristics of the reserve (Muir-Leresche & Nelson 2000; Krug 2001; Naidoo et al. 2016; Taylor et al. 2016).

3.2 Data Informed Wildlife Management and Decision Making

Within conservation and natural resource management, problem solving inherently involves objectives with a set of possible decisions to reach those objectives. When a particular decision is made the other possibilities are naturally precluded (Conroy & Peterson 2013). Depending on the motive, problems, or objectives of a particular situation, different styles of problem framing and subsequent decision making structure are available (Stein et al. 2013; Mendoza & Martins 2006). Historically, natural resource management sometimes faltered as management decisions were not grounded in real data, often lacked robust quantitative analysis, and were in some situations based on personal beliefs or myths (Huettmann 2005; Conroy & Peterson 2013). Structured decision making however clarifies the situation by breaking down the problem, thereby distinguishing individual pieces of the situation and providing more understandable linkages between the management objectives and the possible decisions (Huettmann 2005; Starfield 1997; Conroy & Peterson 2013). While the challenges to this style of decision making have been identified (McLain & Lee 1996), they have also been thoroughly addressed within the literature and the approach's applicability to real natural resource management problems have been explored and supported (Tompkins & Adger 2004; Pahl-Wostl et al. 2007; Chazdon 2008; Gardner et al. 2009; Conroy & Peterson 2013). A structured approach with clear objectives and decision options allows for quick adaption to changing environmental circumstances (Stein et al. 2013), influx of new information from improved data capture and analysis technologies (Huettmann 2005; Sutter et al. 2015; Dodds et al. 2012), and allows for robust incorporation of uncertainties (in data and understanding) inherent to any environmental situation, (Conroy & Peterson 2013; Stein et al. 2013).

One key element of structured decision making is the data in which the logic is grounded (Conroy & Peterson 2013). In any environmentally focused monitoring and management situation, in addition to clear objectives, ongoing data collection and its analysis must be designed to address the questions at hand (Anderson 2001; Lindenmayer & Likens 2010) and measures to determine the impact of management decisions over time need to be clearly defined (Starfield 1997). Uncertainties in the data available to base objectives and decision making on will always be present within any natural system. Methods and strategies have been designed to more robustly account for these uncertainties (Stein et al. 2013;

Mendoza & Martins 2006; Tompkins & Adger 2004), however improved data capture within a system will always improve the ability to make sound management decisions (Conroy & Peterson 2013). The development of advanced technology (e.g. artificial intelligence, remote sensors, big data capture, etc.) presents managers with a plethora of new opportunities to capture data about their systems that were not previously possible (Marvin et al. 2016). Though this influx of new information and technology certainly presents new challenges (Arts et al. 2015; Joppa 2015), it has the capacity to further and deepen understanding thereby improving natural resource management and conservation (Dodds et al. 2012; Lindenmayer & Likens 2010; Maffey et al. 2015).

3.3 Machine Vision

The recent advancements in machine learning technology for object recognition (Krizhevsky et al. 2012; Redmon et al. 2016), known as computer vision or machine vision, has opened the doors to a plethora of opportunities and potential applications of such technology. The aim of machine vision technology is to give computers the ability to understand or comprehend content quickly and accurately solely through visual input (Salahat & Qasaimeh 2017). Applications of machine vision have been explored and developed for a wide range of disciplines and applications including: agriculture (Athani & Tejeshwar 2017; Shakoor et al. 2017), industry and manufacturing (Jahedsaravani et al. 2017; Li et al. 2017), medical sciences (Chi et al. 2017; Lee et al. 2017; Mishra et al. 2017), facial recognition (Holder & Tapamo 2017), law enforcement (Keçeli & Kaya 2017), and augmented reality (Braud et al. 2017). Machine vision technology in conservation and environmental contexts has developed more slowly, however many promising projects (Cohen et al. 2011; Loos 2013; Cohen et al. 2015; Arteta et al. 2016; Wilf et al. 2016; Gomez et al. 2017) have demonstrated the potential of machine vision to a variety of wildlife and environmental situations.

Wildlife and conservation research tasks that are currently limited due to the intensive labour requirements of data processing (Wilf et al. 2016; Maffey et al. 2015) stand to benefit greatly from machine vision automation. For example, camera trapping and aerial photography are useful methods for wildlife studies but are limited because conventional data analysis methods are incredibly labour intensive as imagery must be processed manually (Fegraus et al. 2011). Machine vision technology and automation presents a valuable opportunity to drastically reduce the labour requirements of studies using these projects, thereby saving resources and time for other efforts (Arts et al. 2015; Gomez et al. 2017).

4 METHODS

4.1 Mixed-Methods Research

A mixed-methods research design provided the most robust approach to addressing my main research objectives (Newing 2011). As this research focused on 1) assessing the feasibility of machine vision technology to solve a concrete quantitative wildlife management need and 2) analysing and describing the socio-political space in which this sort of technology would operate using the lens of innovation adoption theory, both quantitative and qualitative methods were necessary.

4.2 Ethics and Positionality as a Limitation

This research was conducted according to CUREC guidelines and with CUREC approval. Both written and oral consent were obtained for all key-informant interviews that were recorded. Interview recordings and transcripts are securely stored within an encrypted database.

Before conducting analysis of information garnered from key-informant interviews, I gave appropriate consideration to the potential limitations of this approach. Although the research question at hand was not particularly controversial or sensitive, the management system under analysis, and that which I aimed to improve, participates in and relies upon consumptive use practices, mainly trophy hunting. While my study did not address the ethics or controversy of hunting directly, the trophy hunting industry has recently come under much scrutiny due to phenomena such as the killing of Cecil the lion (Macdonald et al. 2016) and some members of the community investigated had recently come under fire from international media and activist groups. I recognize that informants may have omitted from their responses sensitive details or may have altered their responses for perceived political correctness (Marshall 1996). I recognize this as a potential limitation to my study, however I did take steps to ensure informants were as comfortable as possible by sharing information, answering questions, and remaining entirely transparent about my research objectives (Chacko 2004). Interview findings were interpreted and analysed in light of these potential limitations and sensitivities as well.

4.3 Machine Vision Model Design

4.3.1 Photo Collection and Data Preparation

To design and train the MVM, a large and quality dataset of annotated photos was needed for training and validation. Annotated photos are manually processed photos where features (i.e. the buffalo) are designated manually within an image and then labelled (i.e. designating what that specific feature is, e.g. male, adult buffalo). In order to prepare this dataset the following steps were followed:

1. First a large set of quality photos was collected, from this a smaller sample set was organised for annotation
2. Buffalo within each sample photo were identified and designated with region coordinates (four X and Y pixel coordinates that form a rectangle around a particular feature within an image) in order to communicate to the MVM where a buffalo was located within an image
3. Finally, the following characteristics of each buffalo designated with region coordinates were assessed: age class, sex, horn spread, and breeding class

Aerial photos were taken from a Savanna S Light Sport Aircraft by either myself or by Oxford MSc candidate #1012577 (from here on referred to as 'candidate #1012577'), using either a Canon 6D (DSLR), Canon T3 (DSLR), or Canon G16 camera ('point and shoot'). When photographing with the 6D, we used either the Canon EF 300mm *ƒ*4L IS USM Telephoto Fixed Lens or the Canon EF 100-400mm *ƒ*4.5-5.6L IS II USM Lens. When photographing with the T3, we used in addition to the previously mentioned lens the Canon EF-S 55-250mm *ƒ*4.0-5.6 IS Telephoto Zoom Lens. We took photographs during eight flights throughout the study area lasting between one and two hours each. Flights occurred between 8 June 2017 and 7 July 2017. Seven flights occurred in the morning hours and one flight took place in the afternoon hours. When flying, photos were taken at heights of 100-300ft. at speeds of 60-70 miles per hour. Buffalo herds were located opportunistically on the day by either flying along known buffalo areas or by flying to locations where they had been seen recently. Once a herd was located the pilot would begin to circle the herd and we would take photographs once the plane was in between the sun and the buffalo herd to ensure adequate photo exposure and to limit the amount of buffalo in shadow. See Figure 3 for illustration, photos were only taken from the green section of the flight path.

As photos were taken, I selected a sub-sample of photos from each flight based upon photo quality and the buffalo composition of each photo. I judged photo quality upon sharpness, exposure (e.g. bright photos with all details of buffalo visible), and focus. Photos with acceptable buffalo composition had the majority of buffalo within the photo visible (fully within frame and not obscured by vegetation) and in a position where most of their body and face were visible. Additionally, photos needed to be framed so that the buffalo were close or large enough (i.e. photo 'zoomed in' enough) to see in sufficient detail the features of the buffalo. Lastly, I strategically selected photos to ensure that all buffalo positions were represented within the training and validation dataset. Photos selected included shots from the front, back, left, and right of the buffalo with varying 'steepness' of the angle at which the photo was taken from the plane (from direct overhead 'bird's eye' view towards a lower more 'eye level' view). An example of a high quality photo selected for annotation versus a low quality photo not selected for annotation is displayed in Figure 4. Photos were usually organised into sets of 10 photos to make the annotation process more manageable.

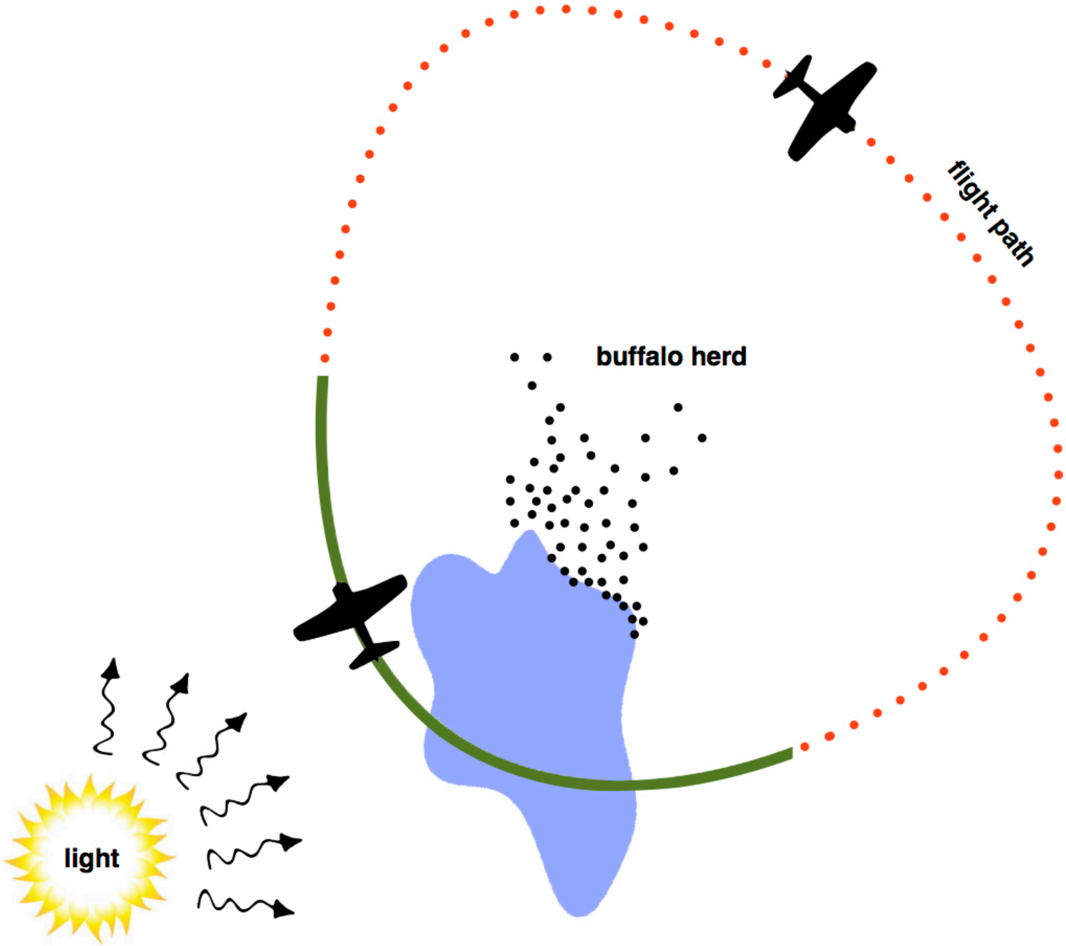

Figure 3: Illustration of flight path for taking photos of buffalo herd. Once a herd was located, the pilot would begin circling the herd as illustrated above and once the plane was between the sun and the herd (as shown by the green section of the flight path), photos were taken. Using this approach, we were able to maximize the number of properly exposed photos collected per flight. The blue patch indicates a hypothetical waterhole, places where buffalo herds were often found.

To designate and classify all of the buffalo within each photo, I used the VGG Image Annotator (VIA; http://www.robots.ox.ac.uk/~vgg/software/via/). After loading a set of images, buffalo were first identified within the photo by drawing 'regions' around each buffalo, which designated X and Y coordinate locations of that buffalo within the photo (Figure 5). For each buffalo, two regions were drawn, one surrounding the entire body of the buffalo and another surrounding just the head, ears, and horns of the buffalo (Figure 6). If only the body or only the head of the buffalo were visible, only one region was drawn for that buffalo (Figure 7a). Regions were drawn in this way even if the buffalo was only partially visible (Figure 7b).

Figure 4: Example of high quality photo selected for annotation (A) versus low quality photo rejected for annotation (B). Photo A is sharp, adequate exposure with little shadowing, few buffalo obscured by vegetation and most of the buffalo are in a position in which the head and horns are visible. Photo B is blurry, with poor exposure and a lot of shadowing, and most of the buffalo do not have their head and horns in view.

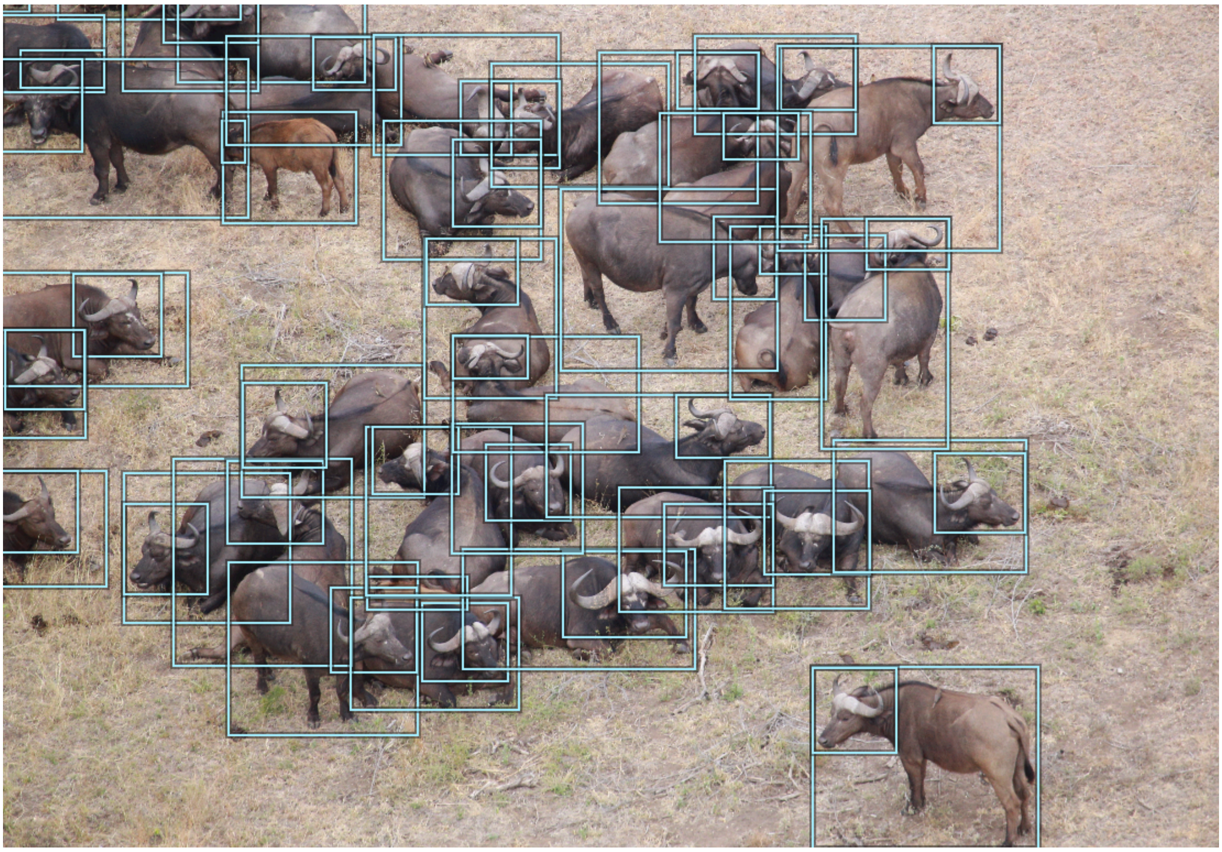

Figure 5: Regions drawn (blue boxes) to designate location of buffalo within each photo.

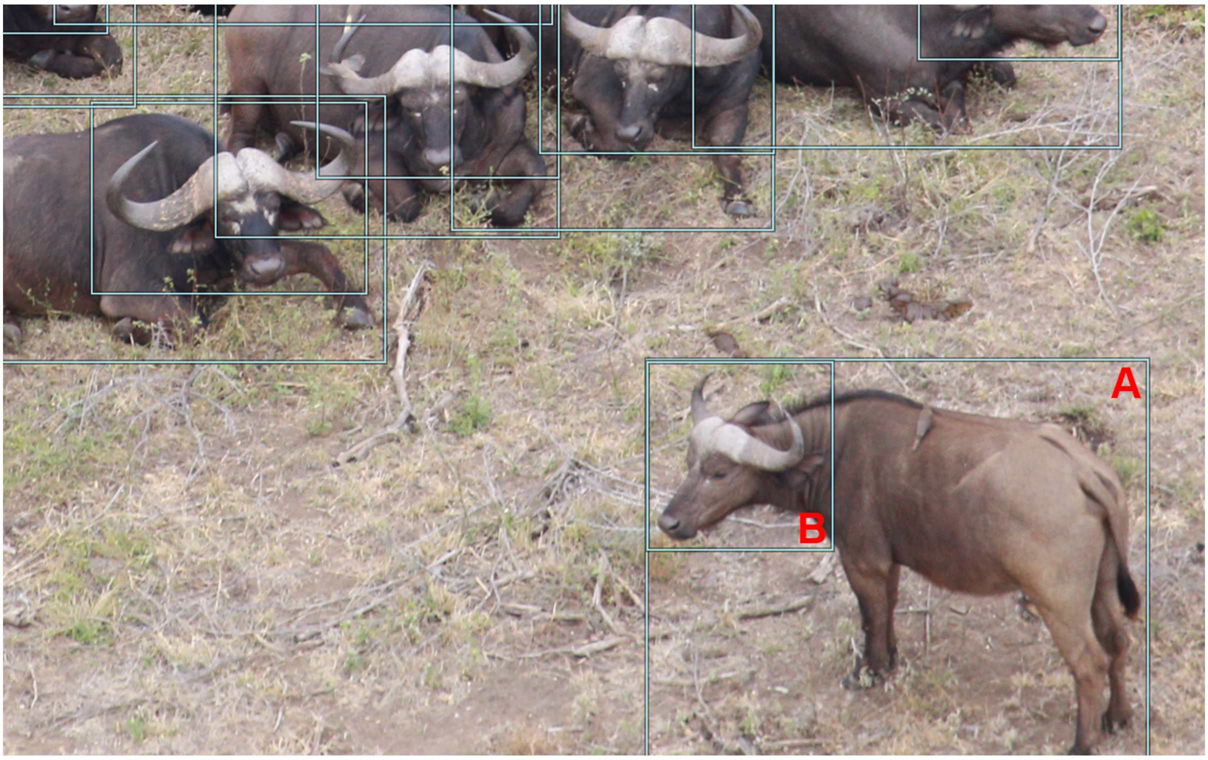

Figure 6: Regions for a single buffalo in bottom right. A labels the region drawn for the entire buffalo and B labels the region drawn just for the head of the buffalo.

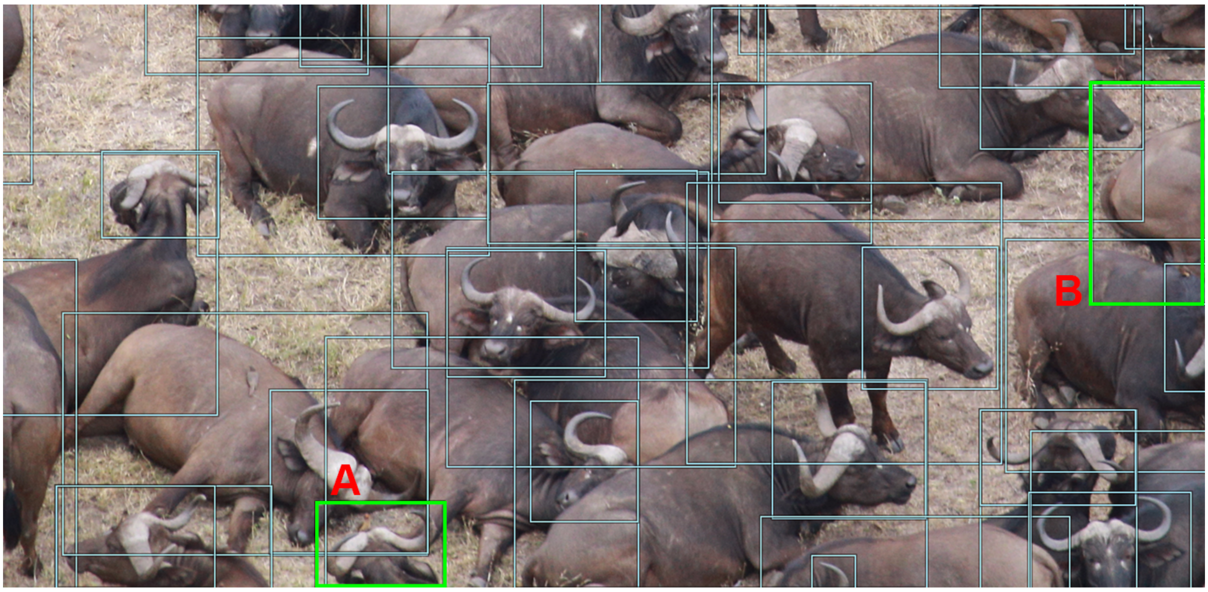

Figure 7: Regions where buffalo are not entirely visible. A shows a region just surrounding the head of a buffalo and B shows a region that just surrounds the rump of a buffalo.

After I completed drawing regions for every photo within a set, the buffalo within each photo were annotated. With the assistance of two of SAWC's Professional Hunting (PH) students, who had been training in the visual assessment of buffalo for an entire year, buffalo were classified into age class, sex, spread class (for adults only), and breeding class (for adult males only). A description of each feature and their possible values are detailed below:

- Age Class (assessed for all buffalo)
  - *Calf*: under 6 years of age
  - *Adult:* 6 or older
  - *Unknown:* age class could not be assessed as not enough of the buffalo was visible
- Sex (assessed for all buffalo)
  - *Male*
  - *Female*
  - *Unknown:* sex could not be assessed as not enough of the buffalo was visible. In the majority of circumstances, the sex for calves could not be assessed.
- Horn Spread (assessed for all *Adult* buffalo): measurement of buffalo horn width from outside edge to outside edge
  - *U3*: under 30 inches
  - *L3*: 30-33 inches (low 30s)
  - *M3*: 34-36 inches (mid 30s)

- *H3*: 37-39 inches (high 30s)
- *L4*: 40-43 inches (low 40s)
- *M4*: 44-46 inches (mid 40s)
- *H4*: 47-49 inches (high 40s)
- *L5*: 50-53 inches (low 50s)
- *SC*: scrum cap (BOTH horns broken off)
- *N/A*: not applicable (for calves, spread cannot be assessed)

- Breeding Class (assessed for *Adult Male* buffalo only): refers to the breeding status (which is a function of age) of adult male buffalo
  - *BB*: before breeding males less than 8 years of age
  - *CB*: current breeding males of 8 years or older but not greater than 12 years of age
  - *PB*: post breeding males of 12 years of age or older
  - *N/A*: breeding class cannot be assessed for females or for calves

4.3.2 MVM Design and Construction

Once the sampled photos had been fully annotated, I sent the photos along with the complete annotation dataset to Arteta for MVM training and validation. For an overview of the design and construction of the MVM please see a technical design overview drafted by Arteta in the Appendix section 10.1 of this paper. The final MVM is intended to perform two primary tasks: 1) to detect and count buffalo within any given image and 2) to assess each of the buffalo detected in step 1 on Age Class, Sex, Horn Spread (for adults), and Breeding Class (for adult males) as to the categories listed at the end of section 4.3.1.

4.3.3 MVM Assessment

Although the previous section's data were prepared to train the MVM to detect buffalo and assess sex, horn spread, and breeding class, we did not have sufficient time to finish the development and training of the full MVM for complete assessment within this paper. Therefore, a less developed version of the MVM capable of detecting buffalo (i.e. finding the buffalo within a photo) was used for assessment. I will refer to this version of the MVM from here on as the 'pilot MVM'. Candidate #1012577 rated the quality of every photo taken onto a scale of one to five, one being the worst quality and essentially unusable and five being the best quality achieved. In order to assess the performance of the pilot MVM, I randomly selected equal sets of photos that had yet to be annotated (as described in Section 4.3.1) from the quality two category and from the quality five category organised by Candidate #1012577. I manually assessed these photos by counting the number of buffalo in each. After I finished preparing this dataset, I ran the pilot MVM using MATLAB® (R2017a) on each photo. In order to perform a preliminary evaluation of the detection performance on full images, I used the mean absolute error (MAE), which measures the absolute difference in the number of detected buffaloes versus the true number of buffaloes present in the scene.

4.4 Key Informant Interviews

I conducted key informant interviews with reserve managers, management practitioners, government representatives, and NGO representatives. Interview participants were sourced opportunistically through the relationships and partnerships established by SAWC, and a snowball approach was used for sourcing additional interview participants. The interviews lasted 15-30 minutes each and all but one were audio recorded. I transcribed, reviewed, and coded all recorded interviews according to themes relevant to the constructs presented within the theoretical framework for innovation adoption and implementation designed by Gallivan (2001)(Figure 1). Immediately following the one interview that was not recorded I noted down key points and reflected upon the interview with the lens of Gallivan's (2001) framework presented in Figure 1. Interview results were analysed with the lens of innovation adoption theory by applying the framework presented in Figure 1, and I placed particular emphasis on identifying and describing any of the facilitating conditions (Gallivan 2001) at play within the space. Furthermore, I aimed to identify the implications of improved practice in Cape buffalo management by understanding the current importance of Cape buffalo, its management, and trophy hunting of the species.

4.5 Management and Hunting Governance Review

Any documents relating to the governance or regulation of wildlife management and trophy hunting practices were obtained and reviewed. I used these documents in conjunction with the key informant interviews to analyse the social, political, ecological, and economic environment in which the MVM would operate and to identify the facilitating conditions that would potentially either promote or hinder adoption of advanced technologies.

5 RESULTS

5.1 The MVM

5.1.1 Aerial Imagery and Annotation Data

In total, we took 3,558 photos during the eight flights. From this set, I selected 663 photos for annotation. Overall, we annotated 14,070 individual buffalo. It is important to note that while 14,070 buffalo were annotated these do not represent 14,070 unique individuals. As multiple photos of a single herd were taken and annotated, there is a considerable amount of overlap in the buffalo represented within this dataset. That is, the same individuals were photographed in multiple different photos. However, each photo resulted in a different composition and therefore every instance of a particular buffalo being annotated delivered new and useful information for training the MVM. Therefore, the results presented below do not necessarily represent the actual population demographic structure of the buffalo herds photographed, but rather the structure of the data used to train the MVM. In summary, 88.2% were adults, 8.7% were calves, and 3.1% could not be classified to an age class (Figure 8). Of the adults 29.6% were male, 46.6% were female, and 23.8% could not be classified to sex (Figure 9). While this proportion of unknowns is high, it is primarily due to the buffalo of an image that are only partially within frame or that are obscured by vegetation.

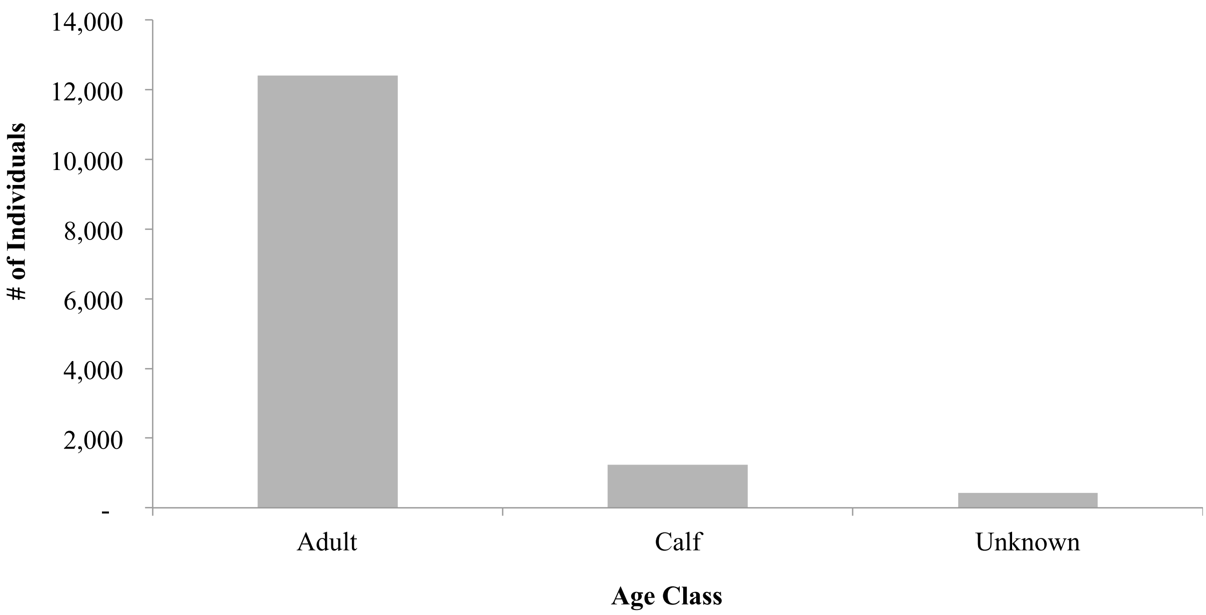

Figure 8: Buffalo age class distribution from the annotation data.

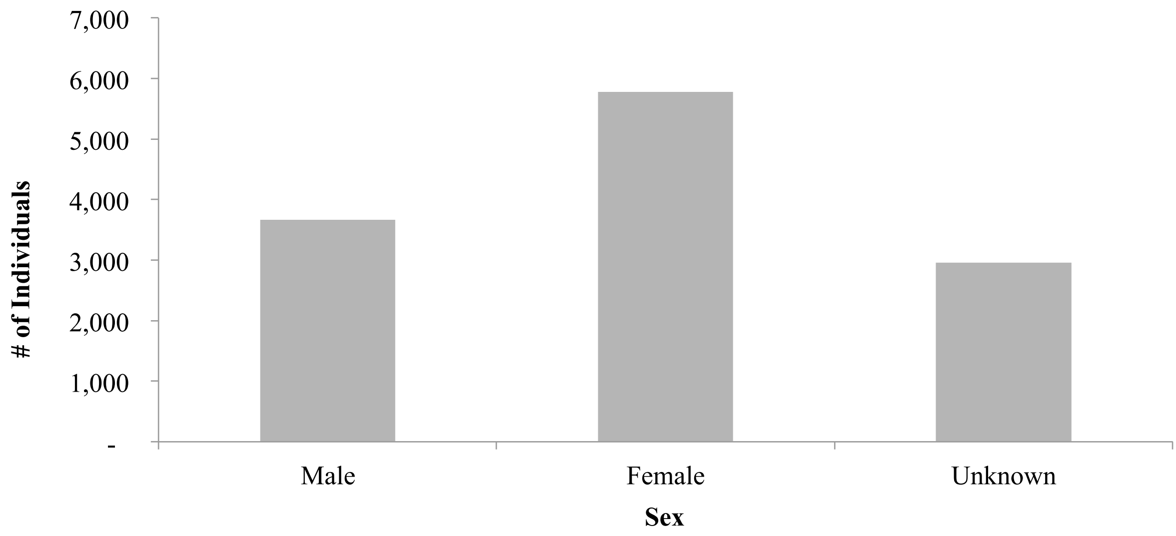

Figure 9: Adult buffalo sex distribution from the annotation data.

Horn spread was assessed for 9,614 buffalo in total. Seven individuals within the dataset were 'scrum caps', meaning both their horns were missing. In total, horn spread could not be assessed for 1,281 buffalo due to obstruction by vegetation or other buffalo, or due to the buffalo being in a position to where the horn spread could not be assessed (e.g. only one side of the buffalo's head could be seen or its head was down in the grass. As expected, the greatest proportion of buffalo fell into the 'low 30s' category (~66%) and only a few individuals (~2.5%) were assessed to be at or above the 'low 40s' category (Figure 10).

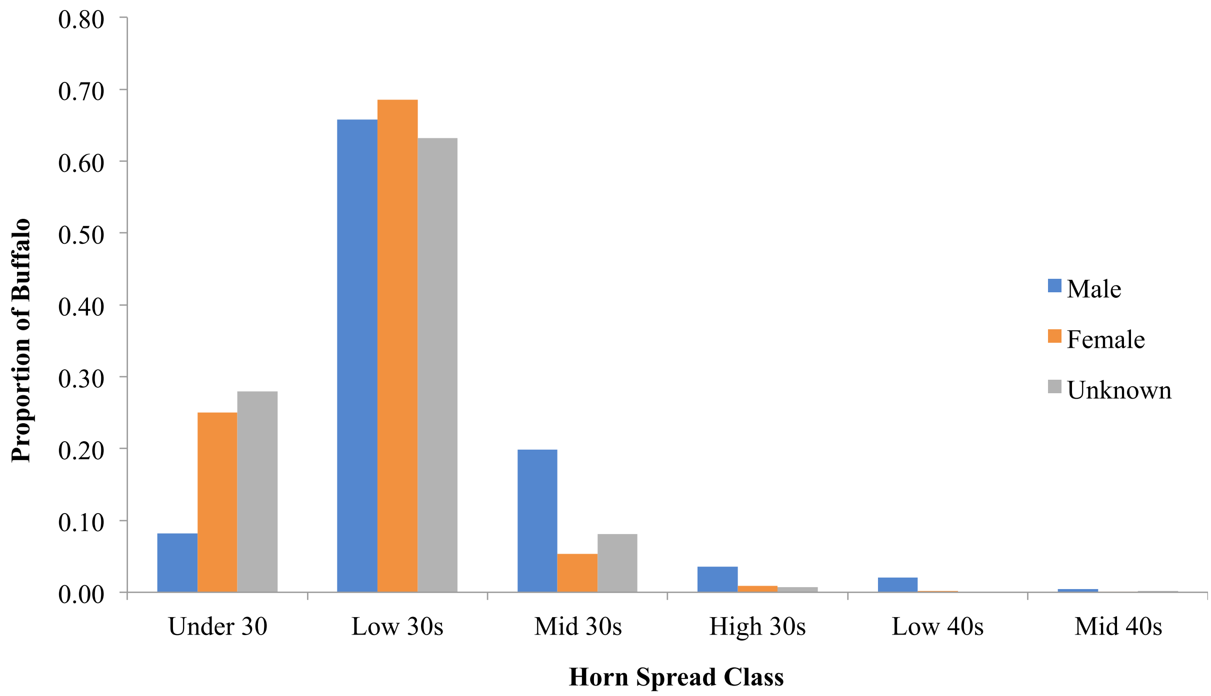

Figure 10: Horn spread class proportions by sex.

Breeding class was assessed for the 3,668 adult male buffalo identified in the set of annotated photos. Of these, 61.3% were classified as *before breeding* males, 35.3% were classified as *current breeding* males, and only 0.5% was classified as *post breeding* males.

5.1.2 MVM Performance

Dr. Arteta reported that initial validation tests of the MVM (run on a subset of data set aside from the original training data for validation purposes) are promising. Detection only had an initial error of 1%. Sex classification had a top-1 error (i.e. the MVM's most confident prediction) of 27%. Spread classification had a top-1 error of 50% and a top-2 (first and second most confident predictions) error of 10%, meaning that the MVM predicted correctly 90% of the time within its first two most likely predictions. Please see Appendix Sections 10.1.3 and 10.1.5 for further details on the performance of the MVM written by Arteta.

5.2 The Pilot MVM

5.2.1 Dataset for Assessment

I randomly selected 60 photos from the quality two category and another 60 photos from the quality five category for assessing the pilot MVM's performance. In total, 3,077 were counted in these 120 photos, 1,786 in the quality two set and 1,291 in the quality five set. Similar to the annotation results from section 5.1.1, of these 3,077 buffalo 86% were adults, 6% were calves, and 9% could not be assigned to an age class. In terms of sex, 50% were female, 28% male, and 23% could not be classified to a sex. However, as seen in Figure 11 there was a lower proportion of unknowns for the quality five category likely due to better image quality.

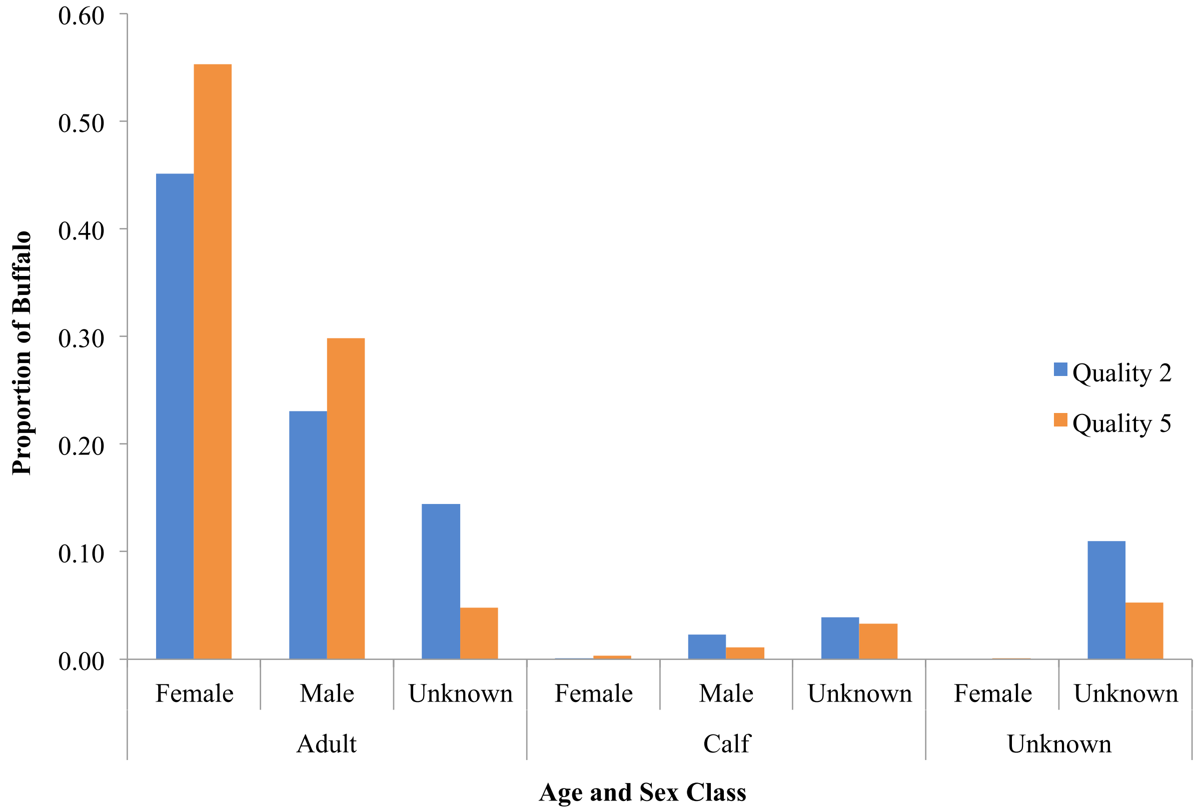

Figure 11: Proportion of buffalo in each age and sex class of the dataset for assessing the performance of the pilot MVM.

5.2.2 The Pilot MVM Assessment

The pilot MVM performed well in detecting buffalo within the images. Buffalo were accurately identified in a variety of backgrounds and from a variety of angels. Figure 12 displays three example images with their corresponding pilot MVM heatmap output (a visual representation of where the computer 'sees' buffalo within an image by masking in black all parts of the image where the computer does not see a target). The photos represent three common image types represented in the aerial image data set: buffalo at a watering hole (Figure 12a), buffalo in mixed bush (Figure 12b), and buffalo lying together in the open (Figure 12c). As demonstrated in this figure, the pilot MVM is capable of identifying accurately the location of buffalo in each varying circumstance. After running the pilot MVM on the two separate sets of photos, there seems to be a clear difference in the performance based upon photo quality. Overall, the pilot MVM resulted in a mean absolute counting error of 10.08 buffalos for the quality two set and 5.22 buffalos for the quality five set, demonstrating a substantial decrease in error with quality five images.

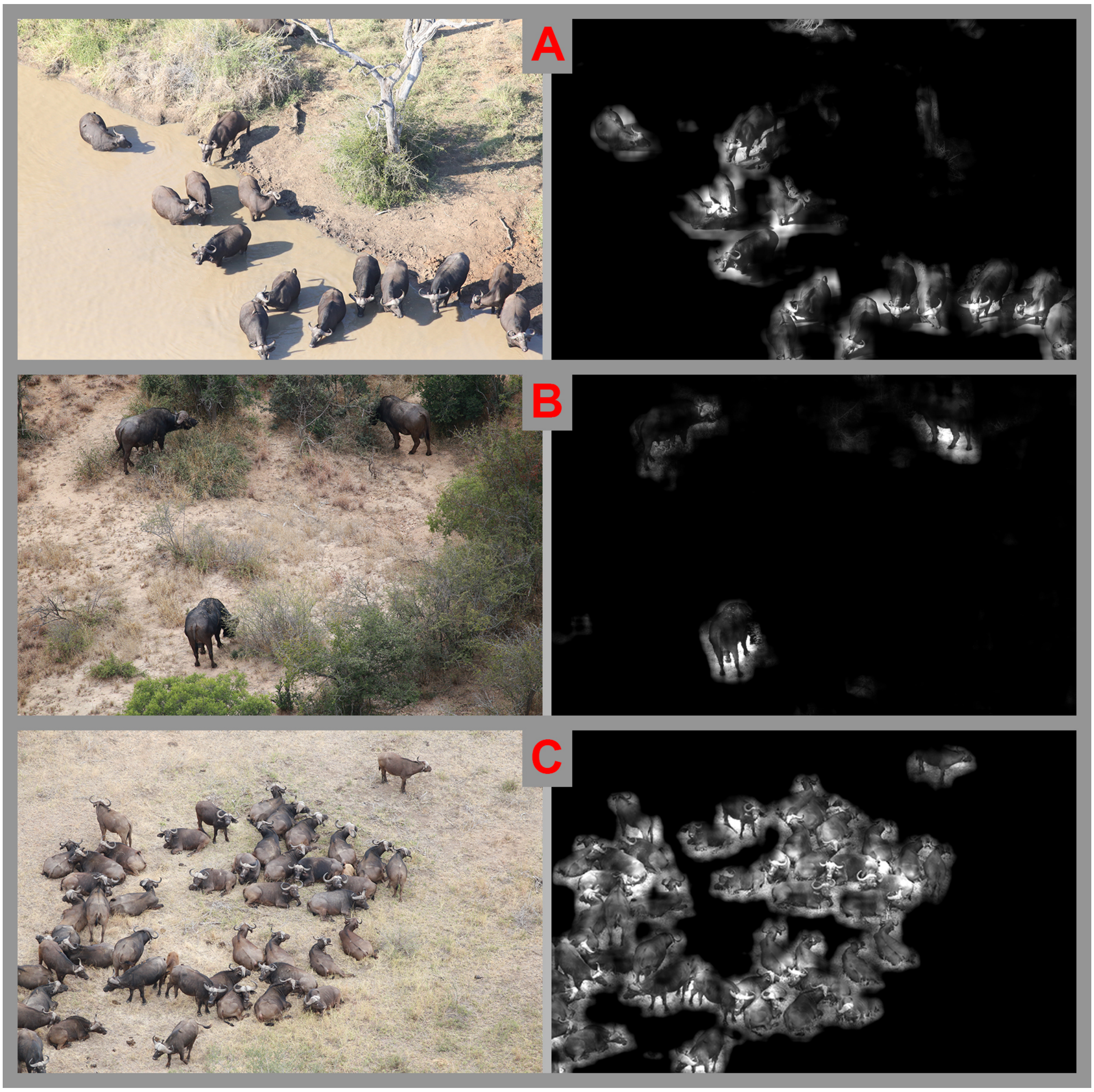

Figure 12: Three example images and the pilot MVM heat map output for each

5.3 Key Informant Interviews

Eight key informants were interviewed to gain insights into the management and making space surrounding Cape buffalo and to elucidate the facilitating conditions for innovation adoption in wildlife management and conservation. I will first summarise findings within four broad categories, and then I will present the key themes emerging from the findings. In addition to the interview findings themselves, I will incorporate findings from my investigation of the management and hunting governance documents (section 4.5). The key document relevant here is the 'Greater KNP Hunting Protocol' (Sowry 2017). This document is prepared by the SANParks Section Ranger in charge of the GKNP in collaboration with representatives of the APNR, and it lays out detailed and concise protocols and guidelines governing the practice and provides justification (the contents of this document are the guidelines and protocols referred to throughout the remainder of this paper).

Table 1 lists the informants and their role relevant to wildlife management and conservation. I will first summarise findings within four broad categories, and then I will present the key themes emerging from the findings. In addition to the interview findings themselves, I will incorporate findings from my investigation of the management and hunting governance documents (section 4.5). The key document relevant here is the 'Greater KNP Hunting Protocol' (Sowry 2017). This document is prepared by the SANParks Section Ranger in charge of the GKNP in collaboration with representatives of the APNR, and it lays out detailed and concise protocols and guidelines governing the practice and provides justification (the contents of this document are the guidelines and protocols referred to throughout the remainder of this paper).

Table 1: List of key informants, their role, and date of interview

Role	Informant ID Code	Interview Date
Manager	I.1_MAN.1	13 July 2017
	I.2_MAN.2	20 July 2017
Practitioner	I.3_PRA.1	12 July 2017
	I.4_PRA.2	20 July 2017
Non-Profit / Organisation	I.5_NGO.1	17 July 2017
	I.6_NGO.2	17 July 2017
	I.7_NGO.3	27 July 2017
Government Representative	I.8_GOV.1	27 July 2017

5.3.1 Management Structure

The interviews with reserve mangers (I.1_MAN.1, I.2_MAN.2) and practitioners (I.3_PRA.1, I.4_PRA.2) provided valuable insights into the organisational and management structure of the private nature reserves and trophy hunting system investigated in this study. The case study system (the APNR) consists of multiple private nature reserves. Each nature reserve is comprised of multiple individual landowners who have collectively agreed to manage their property together as a cohesive reserve. The nature reserve itself and its operations are governed by an executive committee which is representative of the landowners. Each landowner pays a levy each year to contribute to the maintenance of the reserve and the reserve operations. Individual landowners are allowed to utilise their land however they want (e.g. operating a safari lodge, hunting, etc.), but must adhere to the guidelines and regulations established by the nature reserve.

The nature reserve itself is responsible for land and ecological management, conservation and education programmes, and counter-poaching initiatives. The reserve is responsible for raising any budget required to achieve these goals beyond what is provided by the landowners' levies, and many reserves (including the ones studied here) choose trophy hunting as this source of income. Reserves are not responsible for the hunting operation itself, but leases the land and animal usage right to hunting outfitters. Hunting outfitters market hunts and source hunting clients (primarily from the USA and Europe), provide all of the infrastructure necessary during a hunt (camps, staff, firearms, ammunition, vehicles, etc.), hire the professional hunter (the hunting 'guide' directly responsible for the hunting itself and for the client's safety during a hunt), and have complete responsibility over a client's hunting experience. A 'reserve representative' is an employee of the reserve where a hunt is taking place and represents the reserve's interests during a hunt. The reserve representative is responsible for ensuring all hunting protocols and guidelines are followed and ensure that the ethics and sustainability standards of a reserve are respected and adhered to. During a hunt, the reserve representative gives final approval before any individual animal can be harvested. The practitioners interviewed in this study (I.3_PRA.1, I.4_PRA.2) both functioned as reserve representatives.

5.3.2 Data/Knowledge Gap – Recognising the Problem

Though key informants were asked differing questions based upon their role within the system, it became clear that there is indeed a knowledge gap in relation to Cape buffalo and the management of the species. Most informants pointed to a lack of data describing the demographic structure of the buffalo populations as a major obstacle and knowledge gap that current survey methods fail to fill. Additionally, there is a lack of data on the horn spread distributions of buffalo populations (e.g. average spread, largest spread, smallest spread, etc.), which hinders best practice in management and trophy hunting decision making. As stated by one informant,

> *'So we fly over a buffalo herd, we take photographs and then we say okay there's 970 buffalo in that herd but it doesn't say how many are males, how many are*

> *females, how many are adult, how many are what age, how many have what horn width, what have you got?' – I.8_GOV.1*

Additionally there was consensus amongst the informants in regards to an observable decline in the average trophy spread of Cape buffalo. Most informants agreed that this decline is likely due to selective pressure from trophy hunting, however one informant (I.3_PRA.1) disagreed and suggests the decline is more likely due to the severe droughts experienced by the region in recent years (Baudoin et al. 2017). Other participants (I.4_PRA.2, I.8_GOV.1) recognised the droughts as an influential force on buffalo populations, particularly in eliminating the oldest individuals, but not as the primary factor driving the reduction in average horn spread of Cape buffalo populations.

5.3.3 Conservation and Sustainability in Management and Trophy Hunting

Informants agree that historic regulation over trophy hunting was inadequate to ensure genetic sustainability of buffalo populations, and all are generally supportive of the protocols and guidelines that have been established in more recent years to achieve sustainable management. All informants indicated that sustainability is central to management and trophy hunting decision making. Manager and practitioner informants indicated that they had already adjusted management and trophy hunting behaviour and they all expressed commitment to further improving their practices. For example when asked if sustainability is of concern and about the degree they are willing to change their behaviour to achieve it, informant I.2_MAN.2 responded,

> *'We ascribe to that [sustainability] and we believe in that. So if we see that there is a problem in a population, and we've seen it recently in the buffalo, is that we would then adjust what we are going to do… it's got to be sustainable, if it's not sustainable we not going to do it.'*

While informants stressed the importance of trophy hunting, particularly of Cape buffalo, as critical to the funding of reserve operations, they also stressed that making money itself is not the objective of trophy hunting. I.2_MAN.2 stated, 'you know we are not here to make money out of the animals' but explained how without the practice the reserve would be unable to operate at the capacity it does currently as no other source, or even a combination of alternative sources, of income generate as much as trophy hunting. There was consensus amongst the informants that conservation itself is the primary motive of the private nature reserves and that trophy hunting is a means to ensure that the reserves have the resources necessary to achieve their objectives.

The protocols and guidelines governing trophy hunting historically were established by the APNR itself, but now are set by the government and the KNP (I.3_PRA.1). The process of deciding and setting the protocols is, however, still collaborative and reserves assess their populations and request harvest quotas on a yearly basis to be approved by the government (I.4_PRA.2, I.8_GOV.1, I.1_MAN.1). Currently, failure to adhere to quotas and protocols, while not criminal, results in a non-compliant reserve not receiving approval for requested quotas the following season (I.8_GOV.1). While compliance does not seem to be an issue for hunting reserves at the moment, when asked what would happen should it become an issue in the future informant I.8_GOV.1 stated that the government would have to 'take stricter measures and say we [the government] can't support the hunting'. This demonstrates the government's commitment to ensuring that the hunting practices of the participating reserves adheres to the protocols and guidelines in place and a willingness to enact stronger control should it become necessary.

5.3.4 Technology as a Solution

In response to the recognition that this knowledge gap is a problem for Cape buffalo management, most informants indicated that they believe the relevant parties would at least attempt to utilize technology if it were proven accurate enough to be useful. As stated by one informant when asked their opinion as to whether or not new technology would be used,

> *'I think we haven't got a choice, I think we have to [use new technology]. I think we have to be more responsible and we have to demonstrate that we have actually employed science to assist us in our decision making.' – I.1_MAN.1*

While informants recognised the potential for new technology, there were slight differences in thoughts of how the technology would be utilised. Some informants thought that in addition to the approach of this study (designing the technology to be used in assessing aerial imagery to expand the capabilities and output from typical buffalo surveys) technology could be used to assist a reserve representative's decision making on the ground by providing immediate assessment of a target buffalo. Such a tool would enable managers to ensure that targeted buffalo meet the requirements for sustainable harvesting before making the final decision, preventing the problems associated with making too many errors in choosing which buffalo to harvest (i.e. not receiving hunting permits for the following season, or receiving fewer as a consequence - I.8_GOV.1). However, informants I.3_PRA.1 and I.4_PRA.2 (both reserve representatives) expressed concerns as to how this sort of tool would impact a client's (i.e. trophy hunter) experience. Both believed that involving some high-tech tool such as machine vision in on the ground decision making during a hunt would detract from the authenticity and 'traditional Africa' (I.4_PRA.2) feel of the experience. However, both of these informants supported deploying the tool in the fashion that it is being designed for in this study. Additionally, informant I.5_NGO.1 stressed the importance of technology being developed in close collaboration with those who would be using it. I.5_NGO.1 expressed annoyance with similar situations in the past where technology had been designed and delivered to meet a supposed need, but where the designers had failed to collaborate with those who would actually use the technology. This resulted in a product that worked as expected within a design environment but failed to perform on the ground.

5.3.5 The Importance of Trophy Hunting and Cape Buffalo

All informants stressed the importance of trophy hunting to the region. It was identified as the predominant source of income (as much as 61% of operating budget) for the operation of the private reserves that utilise the practice. Without trophy hunting, the informants all agree that the reserves would not be able to operate in the same capacity as they do today and that their conservation programmes would be affected severely. As stated by I.1_MAN.1, 'sustainable use is the crux of what makes these wheels turn'. While non-consumptive tourism (i.e. photographic and safari based tourism) is the other primary source of income generation, for many reserves this form of tourism is either insufficient for meeting their financial needs or unfeasible to utilise as the area encompassed by the reserve is not attractive or accessible to photographic and safari tourists, a conclusion which is also well established within the literature (Lindsey et al. 2006; Mbaiwa 2017). Additionally, trophy hunting provides a much larger proportion of income with significantly less environmental and carbon impact (resources, carbon, etc.). One informant posed a staggering statistic,

> *'We had just over 24,000 photographic tourists that came to the reserve [during the last tourism season], and they raised, with their conservation levies, 17% of our total budget. During the same period of time, we had 54 hunters that came in and they raised 61% of our [budget].' – I.2_MAN.2*

Cape buffalo in particular seem to be a key species for the industry, as it is the primary species hunted and accounts for a majority (around 50% - I.1_PRA.2) of the income generated by trophy hunting (I.1_MAN.1, I.3_PRA.1, I.6_NGO.2). This further exemplifies the concern of the reserves around their impact on buffalo populations and strengthens the system's commitment to finding a solution to the knowledge gap surrounding Cape buffalo.

Furthermore, according to the informants (I.6_NGO.3, I.2_MAN.2, I.8_GOV.1) trophy hunters do not expect the same level of amenities during their stay that non-consumptive tourists do. For example,

> *'A hunter will be satisfied with a far less elaborate camp, he doesn't want fresh sheets and clean towels everyday, he's quite happy with the small little campfire. The photographic tourists they want the more upmarket, they want more, bigger fires, more people, more driving around, more laundry, more everything.' – I.6_NGO.3*

According to the informants, with fewer resources and substantially less impact on the natural environment than other forms of income generation, trophy hunting raises the capital necessary to ensure the continuation of the reserves that use it, and it prevents the landowners from needing to convert their property to some other form of land use (e.g. agriculture or development).

Beyond the financial contributions of trophy hunting, informants described its indirect conservation value particularly from an anti-poaching perspective. With the surge in rhino poaching experienced by the area since 2008 (Rademeyer 2016), reserves and protected areas are struggling to prevent the exponential increase in rhino poaching incidents. In addition to any of the direct counter-poaching efforts deployed, reserves that maintain healthy populations of Cape buffalo and utilise them via trophy hunting provide two forms of inherent protection for the rhinos and other wildlife within that area. First, having a healthy population of Cape buffalo within an area serves as a natural deterrent against poaching activity because Cape buffalo are notoriously dangerous animals and individuals would prefer to avoid areas (if possible) that have known populations of Cape buffalo (I.3_PRA.1). Additionally, trophy hunting as a practice serves as a deterrent against poaching activity because it requires having multiple armed individuals (i.e. the hunting party) operating on the ground at unpredictable times throughout the year (I.7_NGO.3). Additionally, well managed reserves that can deploy their own effective counter-poaching efforts serve as an important buffer area for other protected areas (such as the KNP) that do not practice trophy hunting or that suffer from political corruption (I.1_MAN.1, I.2_MAN.3, I.7_NGO.3, I.8_GOV.1).

5.3.6 Emerging Key Themes

Table 2 lists the key themes relevant to innovation adoption emerging from the interview findings found by constant iteration between the informants' responses and the theoretical framework presented in Figure 1 (Myers 1999). I will use these themes to address the study objectives within the discussion section. These themes are not presented in any particular order and are the result of combining comments of the informants from a wide lens, meaning they may span one or more of the categories discussed previously.

Table 2: Key themes emerging from the interview findings

Theme A:	General acknowledgement that there is indeed a knowledge gap concerning Cape buffalo and agreement that currently no methods exist for filling that gap
Theme B:	Sustainability in utilisation is essential and primary objective of the practice is to ensure continuation of reserve and its conservation initiatives
Theme C:	Continued utilisation of Cape buffalo is vital, but for the sake of sustainability and best practice the system would be willing to self-impose a moratorium on buffalo hunting until sustainability can be ensured
Theme D:	There is an growing concern within the system due to the increasingly intense pressure coming from the international community on trophy hunting as a practice
Theme E:	The result of losing trophy hunting as a practice would be catastrophic to the system and to the conservation of the area
Theme F:	The system is keen for a solution to the knowledge gap and is actively seeking help and assistance
Theme G:	Advanced technology such as machine-vision is foreign and some within the system are sceptical, but remain open to its potential
Theme H:	While failure to follow the hunting protocol is not criminal, doing so would result in not receiving hunting permits for the following season and therefore everyone is committed to doing whatever necessary to ensure that they are in compliance
Theme I:	The organisational structure of the APNR is participatory and decentralised. Actions by one reserve do not dictate that of another. However, 'social' pressure and competition within the system results in some degree of conformity to what others are doing

6 DISCUSSION

This discussion aims to triangulate the results from the mixed-methods approach of the study to gain insights into and to determine the implications of innovation adoption theory for analysing the organisational environment surrounding state-of-the-art technology in conservation and wildlife management. By utilising innovation adoption theory in the case study of machine-vision in Cape buffalo management, I hope to provide foundational contributions to the future development and deployment of state-of-the-art technology in wildlife conservation.

6.1 Proof of Concept

The results from the MVM are sufficient for proof of concept and clearly demonstrate the potential of machine vision technology to provide a solution to the existing knowledge gap within Cape buffalo management. The MVM's detection performance was high, even with very little fine-tuning. Though the performance in classifying sex and spread was not as high, these preliminary performance measures are sufficient to conclude that the MVM is indeed making informed decisions and is not just predicting randomly.

As shown within sections 5.1.1, the data collected to train the MVM is biased towards particular classes for each feature. There were many more adults than calves, the vast majority of adult buffalo were assessed to the L3 and M3 spread classes, and very few Post-Breeding adult male bulls were represented within the dataset. While Arteta was able to handle these data class biases in the design of the MVM, they do present some limitations of the MVM that would need to be addressed in future development. Despite these limitations, with further development, fine-tuning, and additional data, the MVM certainly has the potential to become an accurate and reliable automatic buffalo analysis tool.

6.2 Assessing the Case Study Environment: Ready for Innovation?

Here I will discuss the constructs of the secondary adoption and organisational assimilation processes within the innovation adoption framework presented by Gallivan (2001) shown in Figure 1 and will use the key themes (Table 2) emerging from the interview findings for specific support. Using this lens, I aim to assess the likelihood of the system adopting and implementing the MVM piloted during this study or some other similar solution. While my informants composed a well-rounded representation of the system investigated, these findings are limited in that I do not have complete representation of the entire system and some actors may have differing perspectives. This limitation is incorporated in the interpretation and discussion of my findings below.

6.2.1 Managerial Intervention Intent

Following from Theme A, the general acknowledgement of an existing knowledge gap within Cape buffalo management, one key theme gives solid evidence of the system's intent or willingness to adopt a technology based solution:

Theme F: The system is keen for a solution to the knowledge gap and is actively seeking help and assistance

Cooper & Zmud (1990) identified the importance of rational managerial participation within any successful innovation adoption process. Managers make the initial decision to adopt new technology, provide the resources to ensure that the adoption is successful, and establish the protocols necessary to assimilate the technology into existing operational structures (Leonard-Barton & Deschamps 1988). Chengalur-Smith & Duchessi (1999) identified three key internal and external forces that managers use to consider innovation adoption: environmental, organisational, and technological factors. The system's desire to maintain and improve upon the sustainability of trophy hunting (Theme B) and the need to ensure best practice to maintain scientific credibility in the face of international pressure (Theme D) results in an environment poised well for innovation adoption.

Moch & Morse (1977) and Daft (1978) found that decentralised organisations tend to adopt innovations more rapidly than centralised organisations. The structure of the GKNP and APNR is decentralised in that they are composed of individual reserves and landowners that can act relatively independently from one another within agreed upon bounds. This structure, therefore, lends itself to innovation adoption as individual actors can make the decision to adopt without needing to reach system-wide consensus, which may result in others following suit by force of peer/social pressure if the innovation has the intended success (Lei 2016)(Theme I). The technological factors at play (e.g. the innovation's technical complexity) is certainly a constraining factor to adoption (Tornatzky & Klein 1982) and within this system, concern surrounding these factors is represented by Theme G. However, in this specific case, managers have expressed their interest and have already committed resources (time, data, and, in the instance of one manager [I.2_MAN.2], funding) to developing a solution. Additionally, the piloted technology blends very easily with the current survey methods used by the system. Few changes and additional effort would have to be made to the process that is in place now, limiting the probability of the initiative ending in technology engagement fatigue (Galán-Díaz et al. 2015). Managers recognise the potential of machine-vision technology and understand its potential contribution well enough to support the additional efforts necessary to see it fully developed, clearly demonstrating their managerial intent for adopting a technology based solution to their current problem (Gallivan 2001).

6.2.2 Subjective Norms

Three key themes relating to the subjective norms of the system emerged from the interview findings:

> **Theme C:** Continued utilisation of Cape buffalo is vital, but for the sake of sustainability and best practice the system would be willing to self-impose a moratorium on buffalo hunting until sustainability can be ensured
>
> **Theme D:** Advanced technology such as machine-vision is foreign and some within the system are sceptical, but remain open to its potential
>
> **Theme I:** The organisational structure of the APNR is participatory and decentralised. Actions by one reserve do not dictate that of another. However, 'social' pressure and competition within the system results in some degree of conformity to what others are doing

The experience and skills of the actors within the system are diverse and very well developed, however the penetration of advanced technology into the system has been slow and is to-date quite limited. Theme D represents the actors' hesitations with utilising a new form of technology, however due to the pressing need (Theme A, C) they remain open to any potential solution. Theme C recognises the actors' commitments to doing whatever necessary to ensure best practice, so far as to even temporarily ban or restrict the practice temporarily if deemed necessary. While attitudes represented within this study may not represent those of everyone within the system, the social contagion phenomenon (Lei 2016) paired with the organisational structure of the system pressures individuals more resistant to adopting the technology (Theme I). The subjective norms assessed within this study highlight one key obstacle for innovation adoption, but also layout the action necessary to maximise likelihood of success. By ensuring that any future development works to make a final solution that is as simple to use as possible for non-experts and that blends easily with the current methods used, the concerns about using advanced technology can be surpassed.

6.2.3 Facilitating Conditions

Within Gallivan's (2001) framework Figure 1, facilitating conditions describe any factors that make innovation adoption more or less likely to occur. Many of the themes identified from the interview findings help to describe the facilitating conditions of this system. First, there is a clear knowledge gap hindering best practice and by extension genetic sustainability of Cape buffalo trophy hunting (Theme A). This theme, as it was overwhelming supported by interview informants, makes implementation more likely to occur because the first step to solving a problem is acknowledging it. Furthermore, Theme B, the importance of sustainability in trophy hunting practices, together with Theme C, the importance of continued utilisation of Cape buffalo but willingness to self impose restrictions for the sake of sustainability, form a condition stressing the need for a solution to close the knowledge gap identified in Theme A. Sustainable practice in utilisation requires adequate data describing the influence such practice has on the resource (i.e. buffalo populations) being utilised. As the data available is currently restricted to simple counts and population projections, this condition improves the likelihood of adoption and implementation taking place. Having regular and reliable access to more detailed data would enable better decision making towards sustainability (Theme B), thereby providing better assurance for the practice continuing into the future (Theme C).

Theme E addresses the potential impact of losing trophy hunting as a practice, both to the current system and the conservation of the area. Theme D recognises the pressure on the industry coming from the international community. Together, these themes create a condition stressing the impetus of finding a solution and increase the likelihood of innovation adoption taking place. Though highly controversial as a conservation solution, trophy hunting has demonstrated its effectiveness at providing conservation outcomes (Lindsey et al. 2006; Lindsey et al. 2007; Naidoo et al. 2016) and the effects of it being banned have been disastrous in some areas (Mbaiwa 2017). The system investigated in this study recognises the pressure and power from the international community to alter policies and is taking a proactive approach to ensuring they have credibility to face to this pressure (Theme F).

Theme H describes the governance mechanism at play in the trophy hunting practice of the region. While failure to comply with the established hunting protocol is not a criminal offence (I.8_GOV.1), doing so may result in not receiving permits for the following hunting season or receiving fewer than requested as a consequence. Therefore, participation within the system functions on more of a voluntary basis so although innovation cannot be forced upon individual actors, the need to comply with protocols suggests that individual actors would be open to any tool or method available to assist in assuring compliance. This theme therefore may also function as a condition to support innovation adoption within the system.

Lastly, Theme G, the acknowledgement that advanced technology such as machine vision is foreign to the system and that some are sceptical about its potential but remain open, and Theme I, describing the participatory governance structure of the system, could function as conditions hindering the adoption of innovation. As found by Tornatzky & Klein (1982), the complexity, compatibility, and relative advantage of any technology significantly influences whether or not that technology is adopted. When developing a technology-based solution, developers must pay close attention to the concerns of those that will be using it. Failure to do so would only result in a solution that is impossible or too complicated for practitioners to deploy (Arts et al. 2015; Joppa 2015; Hardisty et al. 2013). Contrary to how Theme I was interpreted in Section 6.2.1, this theme could also pose a challenge as it does carry the risk of only some actors adopting the technology. Within the open system of the GKNP, the wildlife resource is not restricted to a single area of the system and therefore actions by one member of the GKNP can have direct influence over what is available to another. In the instance that only a few members decided to adopt the technology because of the obstacles presented in Theme G or others, it is feasible that very little would result because the improved practice by one member would be negated by the usual practice of the others. This could result in a 'Tragedy of the Commons' (Ostrom 2008) type scenario, leading to abandonment of the innovation.

6.2.4 Bringing It All Together

The private nature conservation system investigated here relies on trophy hunting to fund its operations and conservation initiatives. Without the practice these private reserves would be unable to function in the way that they do today. As stated by I.2_MAN.2 'we are not here to make money out of the animals', but utilising the resource sustainably remains the best method of raising the funds necessary to ensure continued operation of the reserves. The system has become aware of the impacts of genetically unsustainable practices in hunting Cape buffalo (i.e. artificially selecting against the genes for large horns, by harvesting the largest specimens before they have had a chance to breed) and has begun to set in place protocols to reverse this negative impact. While the participating parties are following the protocols, there is currently no method of capturing the data necessary to observe any changes (on a population level) resulting from the new protocols. Managers are very interested in finding a solution to this knowledge gap and recognise that state-of-the-art technology could provide such a solution. Although this sort of technology is foreign to most of the individuals operating within this space, most remain open to its potential. In light of the growing pressure from the international community on trophy hunting practices, reserves that rely on hunting must do as much as possible to ensure that sustainability within their methods are backed by sound science. Not everyone will be on board from the beginning, but the decentralised management structure of the system and the inherent competition within it will likely produce enough social pressure to encourage sceptics to adopt a technology based solution. It is vital that future development initiatives pay close attention to the concerns of non-technology minded individuals if a technology-based solution within this system is to be effective. By approaching the situation with a thorough understanding of the managerial intervention intent, subjective norms, and facilitating conditions of the target system, developers can ensure that technology innovation has the highest likelihood of adoption and assimilation.

6.3 Drawing Out the Implications

The opportunities for technology in wildlife management and conservation are incredibly abundant and technology will drastically change the face of wildlife science and conservation practice in ways that we have yet to understand. This new age of digitally powered conservation that we are on the road towards now, referred to by Arts et al. (2015) as 'digital conservation', is certainly promising but comes with major challenges that must be addressed (Arts et al. 2015; Maffey et al. 2015; Tornatzky & Klein 1982; Galán-Díaz et al. 2015; Kitchin 2014). The novelty of advanced technology in conservation and the opportunities it brings creates an atmosphere that is vulnerable to hype, 'techno-fix' ideology, good news narratives, and untested assumptions (Arts et al. 2015). These potential pitfalls, though understandable, can lead to a conservation initiative wasting time, money, and resources (Joppa & Pfaff 2009). In order to avoid such a situation, conservationists need tools to investigate scenarios where technology may be needed or are significantly beneficial before substantial resources are spent on developing a solution that ends in failure.

In this study I employed a theoretical framework from a vast body of literature surrounding information systems innovation adoption theory, a field entirely separate to conservation (Gallivan 2001; Karahanna et al. 1999; Chengalur-Smith & Duchessi 1999; Moch & Morse 1977; Tornatzky & Klein 1982; Fichman & Kemerer 1999; Lei 2016; Taylor & Todd 1995). With the development of a proof-of-concept machine vision application for Cape buffalo, I have made proactive investigation into a real-world nature conservation system through the well-developed lens of innovation adoption theory (Gallivan 2001). I developed a detailed understanding of the organisational structure, needs, and reservations concerning the potential application of advanced technology to Cape buffalo management, and from this I have identified the challenges and opportunities for technology in Cape buffalo management, gained an understanding of the actors' concerns with using technology, and have assessed the factors promoting and inhibiting the adoption of technology within the system. Utilising the insights gained through this process, technology developers would be best suited to design a solution with the highest probability of adoption by and assimilation into the Cape buffalo management system of South Africa.

Technology has been described as a force that is 'neither good nor bad' (Kranzberg 1986, p.545) and that cannot be controlled, but only guided (Arts et al. 2015). Digital conservation as a force is not yet fully understood (Arts et al. 2015) as it is such a recent addition to conservation practice. Tools for understanding the environments in which this force operates however are necessary for the future of technology in conservation. As of yet, there is little research in this area. Maffey et al. (2015) provides one such tool with the 'Digital Conservation Charter', however though the charter is exhaustive and addresses many key questions, its specificity may miss unexpected factors that arise in certain situations. My study took a broader approach, albeit less detailed, by applying a theoretical framework for analysing the environment in which technology would operate. This method seems advantageous in the very early stages of a technology-based intervention as it is more open-ended and accommodates for the unknowns. By using the lens of innovation adoption during the early stages of the collaborative process, technology developers and conservationists are better informed as to the path ahead and will be better prepared to handle challenges as they come along (Galán-Díaz et al. 2015; Maffey et al. 2015; McIntosh et al. 2011; Joppa 2015).

6.4 Future Directions and Recommendations

In this study, I have demonstrated the potential contributions that innovation adoption theory could make to the future of technology in conservation. Though this theory has been developed within an entirely separate discipline, information technology, its structure accommodates assimilation into the inter-disciplinary field of conservation. One valuable contribution of applying innovation adoption theory is that it could allow for a conservation or management situation to be assessed before any efforts were made to deliver a technology based solution. However, here I worked on developing a preliminary technology based solution alongside the investigation with innovation adoption theory, which potentially skewed my findings to favour the application of the theory. Therefore, further testing and exploration of this theory to conservation is necessary, particularly in cases where a pilot technology is not being developed in conjunction with the investigation. Should this theory prove useful in future studies, efforts should be made as well to develop an adapted version of the theory specifically for conservation and environmental management contexts, making the approach more accessible and useful to conservation researchers and practitioners.

7 CONCLUDING REMARKS

Resources for conservation are severely limited. Optimisation is crucial to maximise the cost-effectiveness of any conservation intervention, including the tools we use. As technology expands and the opportunities for conservation continue to grow, it will be essential to have the tools and methods necessary to optimise the design and implementation of our technology based conservation tools. Conservation will certainly hasten to make use of the innovations of the future, but in certain situations it may not always be the best to do so. Using the lens of innovation adoption theory to assess a conservation problem and the role that a technology solution might play is a promising method to ensure that efforts are carefully directed to best meet the needs of the problem and to identify specific obstacles to be accounted for. This study provides one of the first examples of applying innovation adoption theory to help govern and direct the future of digital conservation.

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10 APPENDIX

10.1 MVM Design, Evaluation, and Future – by Dr. Carlos Arteta

10.1.1 Introduction

The field of computer vision has seen tremendous progress in the recent years due to a new wave of development in the machine learning area of deep learning (e.g. [1]). In particular, Convolutional Neural Networks (CNN) [2], a class of deep learning architectures composed of hierarchical convolutional filters, have been shown to perform exceptionally well across a variety of image recognition tasks [3]. Building on the success of CNNs in vision, we designed proof-of-concept experiments in order to assess the applicability of standard CNN architectures to the task of classifying buffaloes in the wild from aerial images.

A computer vision pipeline for buffalo classification from aerial images would normally consist of two steps. First, individual animals would be detected in order to be able to assess them separately. Then, the characteristics of each animal would be estimated; in this case, such a characterization consisted of assigning each animal into a set of discrete classes related to the measurement of the spread and sex. In a state-of-the-art vision pipeline, both of these tasks would be performed using CNNs.

Due to the generality of deep learning architectures, a general purpose network design can be used for different tasks. Therefore, for both the detection and classification tasks, the standard CNN VGG-M [4] was used. It is also known that deep learning architectures require large amounts of data (e.g. images plus human annotations) in order to learn appropriate filters, but this can be very costly to obtain. A common solution is to use networks that have been previously trained on recognition tasks from large public data sets and then fine-tuned on the smaller but application-specific data sets. In this case, the VGG-M network used was pre-trained on the classification tasks of the ImageNet data set [5].

In this initial study, the required tasks of detection, and subsequent classification, where assessed separately as described below.

10.1.2 Buffalo Detection

The task of object detection in 2D images is generally posed as that of estimating the coordinates of a bounding box that tightly encloses the object of interest, and it is one of the fundamental tasks in the field of computer vision. As the vision field in general, object detection has also greatly benefited from the progress in deep learning, and state-of-the-art systems for detection of objects in images consist of complex deep learning architectures which focus on efficiently proposing candidates for detection and simultaneously assessing them to obtain a score of how well a given candidate represents the object of interest (e.g. [6,7,8]). Nevertheless, in scenes where there is a very high degree of object overlap and occlusion, such as the areal images of buffalo herds, the main difficulty comes from separating the individual instances from each other, which makes standard detection pipelines not directly applicable, and it is still an active area of research in computer vision. Therefore, in this initial study we focused on assessing how well the CNNs can learn to recognize the buffaloes in the images, and provide preliminary proposals for the detection of individuals.

The first step towards the buffalo detector was to train a CNN to recognize the presence of a buffalo on an given image patch. A data set for this task was prepared by cropping 500x500 pixel image patches of buffaloes as well as image patches of random background image regions. This data set was then used to train a VGG-M CNN to do a binary classification task of buffalo or background using a two-class cross-entropy loss function.

Once the CNN was trained, it could be applied to unseen images in a sliding window fashion; that is, the network could process a large (not cropped) novel image by progressively assessing every patch in the image and producing a score map reflecting how likely each location was to contain a buffalo (Figure 1). In these score maps, high values represent high likelihood for the buffalo class.

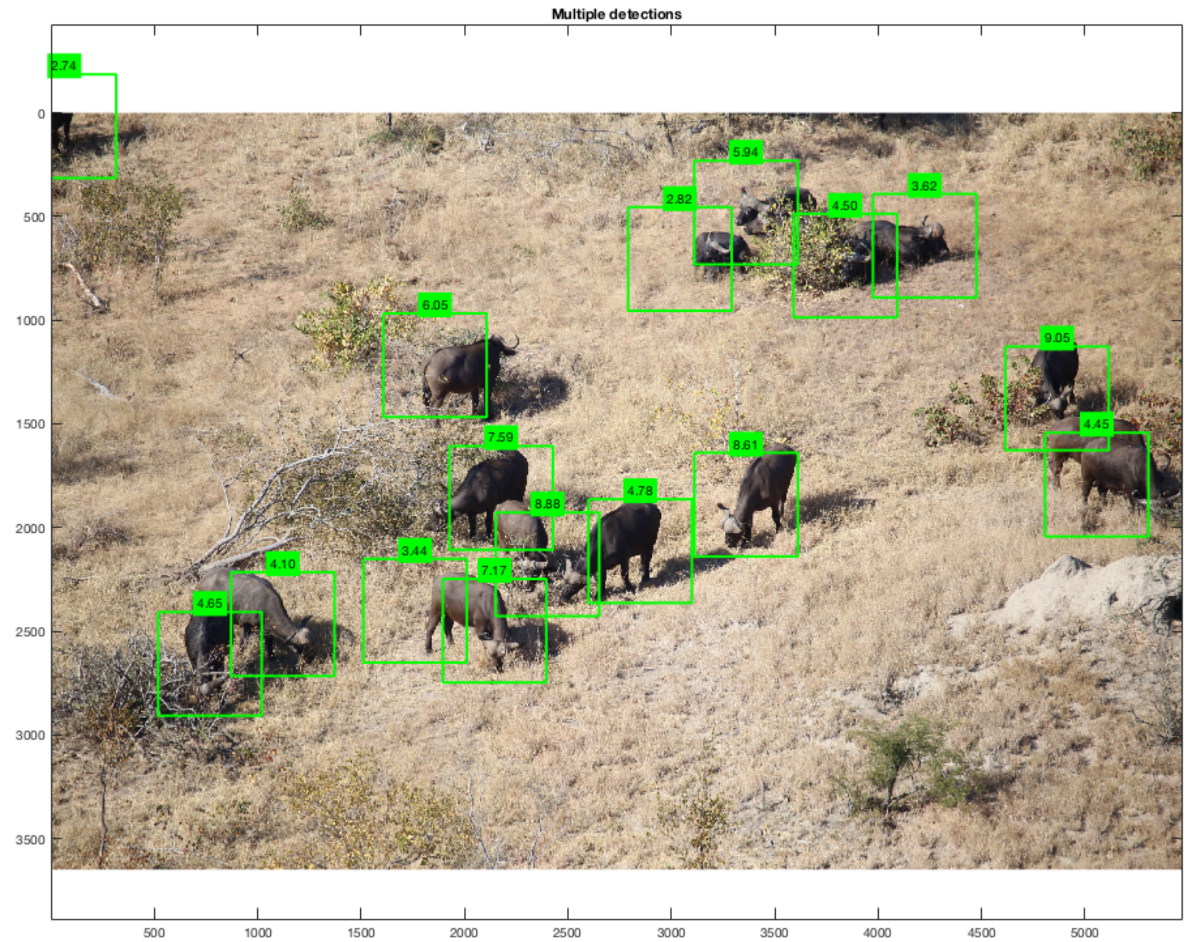

Figure 1: CNN score map exported directly from matlab

Given the score map for buffalo presence, a following step of proposing detection bounding boxes was required. To achieve this, it was assumed an expected size WxH of the buffalo in pixels, and bounding boxes of size WxH were proposed for each high likelihood location in the score map. Such a procedure returns a large amount of high-scoring bounding boxes, which is then reduced using the standard the non-maxima suppression (NMS) procedure. NMS discards the lowest scoring bounding boxes out of those which overlap by more than a user-fixed intersection-over-union score, finally resulting on a set of high-scoring boxes with limited overlap between them.

10.1.3 Buffalo Detection - Preliminary Experiments

The first set of preliminary experiments consisted of predicting the presence of a buffalo over cropped image patches from a held-out validation set (i.e. images not seen during training), as this is the direct objective for which the detection network was trained. These experiments showed a very promising error rate of only 1%. This is mainly due to the relative simplistic visual patterns of the background in the collected data set (e.g. sand, water and trees), making this binary classification task easy to solve for modern vision methods.

On the other hand, the actual detection task of individual instances in large herds is far more challenging than the buffalo presence prediction task, given the issue of overlapping instances described above. Nevertheless, the accurate identification of buffaloes in the full images gives a solid ground for building a robust buffalo detector.

10.1.4 Buffalo Classification

Given an image patch containing an individual buffalo (e.g. as provided by a detection pipeline), the classification tasks consists onf assigning to it a class or label from a discrete set with some semantic meaning. In this proof-of-concept, the aim was to predict the labels from two sets of classes simultaneously: sex and spread.

Similar to the detection step, the VGG-M was trained on 500x500 pixel crops centred at each of the annotated animals. The data set was then cleaned in order to keep only those animals for which both sex and spread had been given a valid label (e.g. discarding uncertain cases). Two cross-entropy losses were used to fine-tune a single VGG-M CNN, one with two classes for sex (i.e. male and female), and one with four classes for spread. The four classes of spread resulted from merging together several of the originally annotated spread classes for which there were only very few examples available, resulting in the following classes: U3, L3, M3 and H3&Above (i.e. a combination of all the spread classes large than M3). At test time, the single classification network is able to produce estimates for both of the classification tasks on previously unseen image patches.

10.1.5 Buffalo Classification - Preliminary Experiments

Classification experiments were performed on a held-out validation set, where cropped buffalo images not seen during the CNN training procedure were assessed to predict sex and spread. In the case of sex estimation, the preliminary experiments showed a top 1 error (classification error rate) of 27%. Meanwhile, spread estimation showed a top 1 error of 50%, and a top 2 error of 10%; that is, when predicting spread, 90% of the time the correct answer is within the top 2 most confident predictions. Although these preliminary classification experiments present error rates that are relatively high, they show that the predictions are significantly better than chance, thus providing a promising start towards an accurate automatic buffalo classifier.

10.1.6 Future Work on MVM

The next step towards building a full pipeline for the buffalo classification task is the integration of the detection and classification networks into a single multi-task convolutional network that is able to propose detection bounding boxes and simultaneously estimate the classes for each of the different label sets. Such a network would have the advantage of not only a more efficient inference process, but also, by sharing a common feature extraction backbone, the detection and the classification network can share the learned visual features of each task boosting the performance for both of them. The integration of these networks should be preferably done within the context of state-of-the-art object detection CNNs (e.g. [6,7,8]) for improved accuracy and efficiency.

Aside from architectural improvements, it is recommended that further training data are collected and annotated such that sufficient samples for each of the classes in each of the classification tasks is well represented. This data set extension would allow the networks to go beyond sex and spread, and learn to provide a complete and automatic buffalo detection and characterization.

10.1.7 References

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