SMART WILDLIFE MONITORING:

EVALUATING A CAMERA TRAP ENABLED WITH ARTIFICIAL INTELLIGENCE

by

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ABSTRACT

Wildlife-livestock conflicts, including depredation, disease transmission, and resource competition, present significant challenges to both the ecological and economic aspects of ranching operations. These conflicts can undermine the sustainability of ranching operations as well as the conservation of wildlife in working landscapes. Leveraging timely and precise data on wildlife activity, distribution, and their interactions with livestock are crucial for enhancing ongoing conflict mitigation efforts and to help sustain wildlife on working landscapes. I evaluated the potential of an artificial intelligence (AI)-enabled camera trap to limit false positive images and provide real-time monitoring of wildlife presence while reducing data overload. In Study 1, I compared the performance of a prototype, edge AI-enabled camera trap (Grizzly Systems) with 2 traditional, non-AI camera traps (Browning and Reconyx) at 8 sites across 3 ranches in south-central Montana, USA, from mid-June through mid-September 2023. I also evaluated the influence of site-specific environmental conditions, including air temperature, wind speed, cloud cover, and vegetation type on camera trap performance. The Grizzly Systems camera trap captured fewer false positive images but exhibited a higher rate of missed detections compared to the Browning and Reconyx camera trap models. Across all 3 camera trap models, the probability of positive detections declined with warmer air temperatures and greater wind speeds. In addition, warmer air temperatures positively influenced missed detections by Reconyx and Grizzly Systems camera trap models, but warmer air temperatures negatively influenced missed detections by Browning camera traps. In Study 2, I compared the performance of a cellular-connected AI-enabled Grizzly Systems camera trap, equipped with an automated image processing and notification reduction workflow, to a traditional, non-AI, cellular-connected Reconyx camera trap at 2 sites in south-central Montana, USA from mid-April to mid-June 2023. The AI-enabled, cellular-connected Grizzly Systems camera trap successfully sent real-time notifications of wildlife presence and transmitted significantly fewer false positive images than the cellular-connected Reconyx camera trap. However, the Grizzly Systems camera trap sent substantially fewer notifications of positive detections than the Reconyx camera trap, which are likely attributed to missed detections by the Grizzly Systems camera trap.

CHAPTER ONE

INTRODUCTION

Estimates of wildlife populations and distributions inform many land management decisions, including setting harvest objectives and assessing the effectiveness of land management interventions (Rabe et al. 2002). Inaccurate estimates of wildlife abundance contribute to poor wildlife management decisions that may harm wildlife, degrade land and water resources, or foment conflict among stakeholder groups, including sportsmen, ranchers, and other landowners. The potential for conflict is especially high in the western United States where many charismatic wildlife species inhabit large, unfragmented landscapes provided by working lands (e.g., farms, ranches, and multiple-use public lands; Western et al. 2020, Hovick et al. 2023). Additionally, an important strategy for wildlife conservation in the American West is to maintain the economic and social viability of working lands (Haggerty et al. 2023, Hovick et al. 2023). Accurate estimates of wildlife abundance and their distributions are an important step in mitigating conflicts, which, in turn, help sustain wildlife populations in working landscapes.

Camera traps are a common tool used to survey wildlife, and are widely accepted, non-invasive, and can be less labor-intensive than many other survey methods (Cutler and Swann 1999, Burton et al. 2015). However, camera traps are not without their own challenges. The passive infrared (PIR) sensors used by most modern camera traps are susceptible to false positive triggers, where non-animal thermal heterogeneity in the detection zone causes the camera trap to capture an image that does not contain an animal (Welbourne et al. 2016). False positive images and the generally large quantities of images associated with camera trap surveys can be problematic for timely data processing and analysis (Swanson et al. 2015). The elimination or reduction of false positive images could greatly improve the efficiency of camera traps.

Another challenge with using camera traps is the variability in performance among different camera trap models and under differing environmental conditions that have direct effects on population estimates modeled from camera trap data. Some aspects of camera trap performance that may influence detection probabilities and the subsequent accuracy of modeled wildlife population estimates are understudied (Burton et al. 2015, Hofmeester et al. 2019). Abundance modeling and occupancy modeling are examples of contemporary wildlife survey methods that are well-suited to data obtained from camera trapping, but require an estimate of detection probability (e.g., MacKenzie et al. 2002, Royle and Nichols 2003). Inaccurate estimates of detection probability can bias modeling results. Environmental conditions such as air temperature or vegetation obstruction are acknowledged to have varying effects on detection probabilities, while the effects of other variables, such as cloud cover and wind speed, are not well understood (Swann et al. 2004, Moll et al. 2020). Greater understanding of how camera trap performance varies under different environmental conditions will contribute to more accurate estimates of wildlife population size and distribution.

Finally, recent developments in camera trap technology that connect camera traps with cellular or satellite networks create opportunities for real-time wildlife monitoring (Dertien et al. 2023, Tulasi et al. 2023, Whytock et al. 2023). There are many possible applications of real-time wildlife monitoring where active wildlife management is desired, especially in mitigation of human-wildlife conflict, such as poaching or livestock depredation. Connected camera traps are still in the early stages of scientific assessment, but they appear to hold comparable potential to unconnected camera traps in producing overwhelming amounts of data (Whytock et al. 2023). As connected camera traps are increasingly used in applied management scenarios, it is essential that they include workflows to automate data processing and minimize the amount of superfluous data received by an end-user.

The Grizzly Systems camera trap is a new, never-before-tested camera trap with an artificial intelligence (AI)-enabled passive infrared sensor that reduces false positive images. The Grizzly Systems camera trap can also be connected to cellular networks and send real-time notifications. The goal of my research was to evaluate the performance of the Grizzly Systems camera trap and its ability to reduce false positive images while maintaining positive detections, as well as assess several environmental factors that may affect camera trap performance. I also evaluated cellular-connected Grizzly Systems camera traps with an automated data-processing workflow. The objectives of my study were to:

1. Assess the performance of the Grizzly Systems AI-enabled camera trap by comparing it with two traditional, non-AI camera traps.
2. Evaluate the effects of site-specific environmental conditions on camera trap performance.
3. Assess the performance of the cellular-connected Grizzly Systems camera trap and automated image processing workflow by comparing it with a non-AI-enabled cellular-connected camera trap.

CHAPTER TWO

LITERATURE REVIEW

Accurate estimates of wildlife populations and their distributions across landscapes are essential for informed species management and decision making. A wide array of analytical methods has been developed for population estimates, with advantages and drawbacks for each method depending on the species of interest and the environment (Williams et al. 2002). Some methods (e.g., point counts) have become well known as robust means of data collection for various population estimates (Pierce 2020). However, field-based abundance estimation can be labor-intensive, cost-prohibitive, or ineffective when studying populations of reclusive, nocturnal, or low-density species (Vine et al. 2009, McCallum 2013). Camera trapping has become a widely accepted, non-invasive method for surveying the distribution, behavior, habitat use, and size of wildlife populations (Karanth and Nichols 1998, Cutler and Swann 1999, Tobler et al. 2008, Kays et al. 2009, Burton et al. 2015).

The earliest form of camera trapping for wildlife research was first recorded in 1927 when scientist Frank Chapman used a camera triggered by a trip wire to survey faunal species on the newly designated research island of Barro Colorado (Chapman 1927 in Kucera and Barrett 2011). By the 1960s, advancements in photography equipment allowed researchers to leave camera traps in the field for short periods (Kucera and Barrett 2011). By the 1980s, camera traps had become commercially available (e.g., used by hunters), and scientists had developed early analytical methods that used camera trap data for various research questions, such as a precursor to capture-recapture modeling (e.g., Seydack 1984). Active infrared sensors were developed in the early 1990s, in which an infrared beam functions as an invisible trip wire. When something crosses the path of the infrared beam, the camera triggers and takes a picture (Cutler and Swann 1999). Passive infrared (PIR) sensors were also created in the mid-1990s and are now the most common sensor type used in commercial camera traps available for research, management, or recreation (Cutler and Swann 1999, Trolliet et al. 2014). PIR sensors function by monitoring emitted infrared radiation by surfaces (surface temperature) within the camera trap's detection zone (Welbourne et al. 2016). When there is a rapid change in temperature, such as an animal passing through the detection zone, the PIR sensor creates an electrical charge that triggers the camera to take a photograph (Welbourne et al. 2016).

Camera traps are used today for many of their original purposes, but advances in applied statistical methods for modeling population and community parameters of interest (e.g., MacKenzie et al. 2002, Royle and Nichols 2003) have made the use of camera traps increasingly prevalent in wildlife monitoring and research. In some situations, camera trapping is advantageous over other survey methods, as camera traps allow for longer or more frequent sampling periods with less field effort and are less invasive than some traditional survey methods (Hamel et al. 2013). Like other survey methods, camera trap surveys must be carefully designed so that they meet the assumptions of statistical models used for analysis and avoid biasing population estimates (Hamel et al. 2013).

Impact of Camera Trap Deployment Techniques

Essential aspects of camera trap survey design include factors such as camera trap site selection and distribution, camera trap height, and decisions about the use of artificial attractants, all of which depend upon the species of interest and study objectives. When selecting camera trap site locations, some wildlife species commonly use linear features such as roads, game trails, or fault lines for travel, whereas other species avoid linear features (Trolle and Kéry 2005, Iannarilli et al. 2021). For example, Iannarilli et al. (2021) observed that wolves (*Canis lupus*) and bobcats (*Lynx rufus*) had higher detection probability at camera trap sites placed on trails and undeveloped roads, but other species, such as fisher (*Pekania pennanti*) and black bear (*Ursus americanus*), had higher detection probabilities at camera trap sites placed in random, non-trail sites with scented lure. In a study of the elusive giant pangolin (*Smutsia gigantea*), Matthews et al. (2023) documented higher detection probabilities when camera traps were targeted on burrows compared to other landscape features (termite mounds, trails, etc.). Optimal camera trap locations will vary according to species' behaviors in order to maximize detection probability, but multi-species surveys should incorporate multiple site selection strategies so as to not bias results due to differences in resource selection among species (Iannarilli et al. 2021, Matthews et al. 2023).

The use of artificial attractants such as baits or lures at camera trap sites is debated among researchers. Artificial attractants can increase the detection probability of wildlife as well as improve identification of individual animals by encouraging wildlife to linger in front of the camera trap. Adequate imagery of individually identifiable animals is important for capture-recapture studies (du Preez et al. 2014, Zimmermann and Foresti 2016, Stewart et al. 2019, Buyaskas et al. 2020). However, baiting camera trap sites can significantly increase the labor and cost of camera trap surveys (Balme et al. 2014), as well as modify the behavior of some species, which could potentially confound studies on intraguild interaction or violate assumptions of some population models (e.g., geographic closure, equal detectability; Rocha et al. 2016, Newbolt et al. 2017, Mills et al. 2019). There is also concern about baits causing habituation, which can increase the likelihood of negative human-wildlife interactions (Balme et al. 2014).

Camera trap height is usually based on the species of interest, with the general recommendation being to place the camera traps at the height of the largest part of the target species' body (usually 0.3 – 2m; Meek et al. 2012). However, fast-growing vegetation or heavy snow can interfere with camera traps when they are placed close to the ground, and these conditions should be considered when designing a survey (Zimmermann and Rovero 2016). Theft by humans or destruction of camera traps by inquisitive wildlife or livestock can also be problematic. Current recommendations for studies where camera traps are at risk of theft or damage are to use informational signs, or to place camera traps in lock boxes that protect the camera trap body and inhibit access to the attachment mechanism (Meek et al. 2016). Meek et al. (2016) and Jacobs and Ausband (2018) explored placing camera traps higher (~3 m, angled downwards), which makes camera traps inaccessible to most wildlife and less easily seen by humans, and therefore more resistant to destruction or theft compared to camera traps placed at lower heights. This tactic produced mixed results. Meek et al. (2016) observed that camera traps placed at 3.5 m had fewer detections than camera traps placed at a more standard height (0.9 m), whereas Jacobs and Ausband (2018) documented no difference in detection rates between low (0.6 m) and high (3 m) camera traps. Jacobs and Ausband (2018) suggested that the discrepancy between studies may have been related to differences in deployment tactics, size and guild of species detected, amount of data collected, and weather differences (e.g., average temperature). Some manufacturers are also developing camera traps that have a much smaller profile and are easier to camouflage than traditional camera traps, which may aid in preventing theft (Dertien et al. 2023).

Effects of Environmental Conditions on Camera Traps

Camera traps using PIR sensors monitor surface temperatures within their detection zones for significant changes in temperature resulting from an animal moving into the detection zone (Welbourne et al. 2016). By principle, PIR sensor function assumes a homogenous background and relatively even temperatures within the detection zone when animals are not present. However, in field settings, the environment within the detection zone is often highly heterogenous, and subject to uneven heating. This heterogeneity makes PIR sensors susceptible to false positive triggers, where movement of non-animal objects (e.g., vegetation) in the detection zone causes the camera trap to trigger (Welbourne et al. 2016). Depending on the sensitivity of the camera trap model (i.e., the threshold of temperature difference needed for the camera trap to trigger), the rate of false positive images can be very high (Heiniger and Gillespie 2018). False positive images become problematic at high rates, as they occupy storage on the camera trap's SD card and waste battery power, as well as increase the amount of time needed to process images (Newey et al. 2015, Heiniger and Gillespie 2018). However, decreasing the PIR sensor's sensitivity increases the risk of missed detections, where an animal passes through the detection zone but does not trigger the camera trap. Depending on the species of interest (e.g., small or rare species), decreasing PIR sensitivity may not be a viable option (Heiniger and Gillespie 2018).

Environmental factors affect the heterogeneity of the detection zone, which, in turn, could impact whether the camera trap triggers and the overall capture rates of positive detections and false positive images (Newey et al. 2015, Hofmeester et al. 2019, Moll et al. 2020). Few studies have directly evaluated the impact of environmental variability on camera trap performance, but abundance or occupancy models often incorporate measures of environmental factors, such as temperature and vegetation cover type, into estimates of detection probability (Lesmeister et al. 2015, Rich et al. 2016, Moll et al. 2020).

Similar wildlife survey tools, such as infrared thermal imagers, may also be informative about the impact of environmental conditions on camera traps (Havens and Sharp 2015). Both PIR sensors and infrared thermal imagers measure emitted radiation, which may make inferences about the performance of thermal sensors helpful. In general, vegetation cover, air temperature, humidity, wind speed, and cloud cover are known to negatively affect the quality of thermal signature of wildlife as captured by a thermal imager and increase the amount of thermal clutter that can be caused by the surrounding landscape (vegetation, bare ground, rocks, etc.; Havens and Sharp 2015). The increased thermal clutter discussed in the context of thermal imagery likely translates into an increase in heterogeneity within the detection zone of a camera trap.

Vegetation

Viewshed obstruction by vegetation can decrease camera trap detection rates of wildlife, although the effect varies by species (Moll et al. 2020). For example, detection rates decreased with increasing vegetation obstruction for squirrels (*Sciurus carolinensis* and *S. niger)*, racoons (*Procyon lotor*), red foxes (*Vulpes vulpes*), Virginia opossums (*Didelphis virginiana*), and white-tailed deer (*Odocoileus virginianus*), but not for striped skunks (*Mephitis mephitis*), coyotes (*Canis latrans*), or domestic cats (*Felis catus*; Moll et al. 2020). Greater amounts of vegetation can also increase the number of false positive images. If vegetation within the camera trap's detection zone heats unevenly and moves (e.g., due to wind), it can cause the camera trap to trigger and capture a false positive image (Gregory et al. 2014). One potential solution for short-term camera trap deployments is to remove vegetation within a certain distance from the camera trap, but this may be impractical when camera traps are left unattended for long periods of time during the growing season.

Weather Conditions

Warmer air temperatures may reduce detection probabilities by decreasing the temperature differential between the surface of the detection zone and the surface of an animal (Swann et al. 2004, Welbourne et al. 2016, Jacobs and Ausband 2018). Relative humidity or precipitation may also negatively affect camera trap performance. Kays et al. (2009) and Rowcliffe et al. (2011) reported shorter detection distances during the rainy season in Panama, with the detection distance being as much as 70% farther during the dry season (Rowcliffe et al. 2011). The effects of other environmental conditions, such as cloud cover, on the detection rates of camera traps have not been evaluated. However, cloud cover likely shields the detection zone from solar insolation, creating a more homogenous background (Havens and Sharp 2015). A more homogenous background may facilitate a reduction in the number of false positive images.

Operational Differences Among Camera Trap Models

Not all camera traps are constructed the same. For example, camera trap models can vary in PIR sensitivity (i.e., threshold of thermal difference that results in the camera trap triggering), the size of the camera trap's detection zone, and the trigger speed, which is the time between the PIR sensor detecting a thermal anomaly and the camera trap triggering (Swann et al. 2004, Wellington et al. 2014, Zimmermann and Rovero 2016). Different camera trap specifications provide different advantages depending on the wildlife survey goal, but if multiple camera trap models are used in a single project, variability in detection rates caused by differences in camera trap function must be accounted for during data analysis (Damm et al. 2010, Swan et al. 2014, Burton et al. 2015, Hofmeester et al. 2019).

Studies quantifying differences between specific camera trap models are difficult, because camera trap technology changes frequently, often outpacing the publication of research (Zimmermann and Rovero 2016). However, there are several examples of studies specifically examining camera trap function. Swann et al. (2004) compared 6 different camera trap models manufactured by Trailmaster, DeerCam, CamTrakker, and Buckshot to evaluate factors influencing detection. Camera traps with a wider detection zone were more likely to capture false positive images, and a camera trap deployment height of 120 cm missed detections of small- and medium-sized animals when compared to a deployment height of 20 cm. Weingarth et al. (2013) evaluated 6 PIR camera trap models for their utility in capture-recapture studies of Eurasian lynx (*Lynx lynx*). The authors evaluated camera trap models manufactured by Cuddeback, Bushnell, and Reconyx. Only one Cuddeback model was adequate for visual identification of individual lynx. Of the 5 remaining camera trap models evaluated, one was inadequate due to unreliability (failed triggers), and the other 4 did not have high enough image quality to identify individual animals (Weingarth et al. 2013). More recently, Palencia et al. (2022) evaluated the detection probabilities of 5 different PIR camera trap models in a field setting by comparing them with continuous video and observed that camera trap model significantly impacted detection probability. Camera trap models manufactured by Bushnell and Ltl Acorn had a greater probability of detection than models made by KeepGuard, Reconyx, and Scoutguard (Palencia et al. 2022). Greco and Rovero (2021) documented that Browning camera traps had higher detection probabilities compared with Cuddeback or UOVision in their study of the African golden cat (*Caracal aurata*). Swearingen et al. (2023) observed no difference in the number of animal detections among Browning, Reconyx and Moultrie, but did document that Moultrie was less reliable than Browning or Reconyx, as a significant proportion of Moultrie camera traps were not functional for the duration of the study due to short battery life. Swan et al. (2014) compared the effectiveness of Reconyx and Scoutguard camera traps for studying ground-dwelling mammals in Australia and documented better detection rates in Reconyx camera traps.

Processing Data Collected by Camera Traps

Wildlife population monitoring with camera traps can generate thousands of images that must be sorted and annotated. That is, each image is examined to determine whether it contains an animal and, if so, the animal in the image is identified and the image is labeled or sorted in some manner (Swanson et al. 2015). The process of annotating images is time-consuming and can significantly delay subsequent data analysis (Newey et al. 2015). Some projects, such as Snapshot Serengeti – a long-term wildlife monitoring project in Africa that has produced millions of images – have enlisted the help of citizen scientists to annotate images, but annotation can still take several months before data collected by camera traps is ready for statistical analysis (Swanson et al. 2015, Anhalt-Depies et al. 2019, Willi et al. 2019). The delay between the collection of data and their processing can limit the usefulness of inferences made if they are not accomplished within a time-frame relevant to the management of wildlife species or their habitat (Merkle et al. 2019).

Nazir et al. (2017) developed a user-customizable camera trap that incorporated confirmatory sensing technologies (microwave radar and edge image processing) to analyze camera trap images to reduce missed detections and false positive images. Identified false positive images were placed in a separate folder on the SD card or deleted entirely. The radar sensor could be used in concert with the PIR sensor, but doing so resulted in delays in image capture that could cause missed detections (Nazir et al. 2017).

Machine Learning for Image Processing

Researchers are increasingly turning to computer-vision machine learning (ML) programs to efficiently reduce image processing times in ecological studies. Some studies have reported reducing image processing times to hours or days (compared to months; e.g., Tabak et al. 2020). While open-source ML algorithms such as Machine Learning for Wildlife Image Classification in R (Tabak et al. 2020) offer accessibility, challenges arise with accuracy in diverse locations or small training datasets (<500 images/class). Object detection models such as MegaDetector, which classifies images into broader categories of animal, vehicle, or person, rather than species-specific classifications, provide high accuracy in identifying objects across diverse backgrounds. However, MegaDetector faces limitations in classifying images with wildlife that are far away from the camera trap (Beery et al. 2019, Leorna and Brinkman 2022). To address the lack of species-specific classification, Fennell et al. (2022) used a combined workflow that employed MegaDetector to filter blank images, and human verification for species-specific annotations and uncertain object detections. This approach demonstrated a remarkable 500% increase in data processing efficiency (Fennell et al. 2022).

Cellular- and Satellite-Connected Camera Traps

Another current drawback to the use of many camera trap models is that camera trap data is not real-time, reducing the utility of camera traps in situations where active wildlife management is desired (e.g., conflict prevention, anti-poaching efforts; Whytock et al. 2023). Although all camera trap models provide valuable information on wildlife presence, management actions focused on reducing conflict are often less effective due to this lag in information relay. In response, many manufacturers have developed camera traps with cellular or satellite network connectivity that can provide camera trap images in real-time. In areas with cellular coverage, this connection enables remote viewing of low-resolution images sent by the camera trap to a phone, internet application, or email. To date, few studies have used cellular-connected or satellite-connected camera traps for scientific research (but see Dertien et al. 2023, Tulasi et al. 2023, Whytock et al. 2023). Camera trap projects using data connection have an associated cost increase related to camera trap equipment, network connection, and data transfer. If camera traps were to capture large numbers of false positive images, data transfer over a network could become inefficient and cost-prohibitive.

Camera Traps Integrated with Machine Learning

Camera traps integrated with machine learning provide another way to reduce data processing time and reduce the volume of false positive images. After capturing an image, “smart” camera traps use edge artificial intelligence (AI) to automatically classify the image (Dertien et al. 2023, Tulasi et al. 2023, Whytock et al. 2023). Then, when combined with cellular or satellite network connectivity, connected camera traps can send users real-time or near real-time notifications of wildlife presence. For example, Dertien et al. (2023) described using

Trailguard AI camera traps for preventing human-tiger (*Panthera tigris*) conflicts in India. The camera traps used edge-AI image classification and cellular network connectivity to send real-time notifications of tiger and human detections to email or a smartphone application (e.g., Telegram or Whatsapp; Dertien et al. 2023). Tulasi et al. (2023) created an edge-AI system trained to identify mountain lions (*Puma concolor*) and bobcats (*Lynx rufus*) that was compatible with existing (non-connected) camera traps in concert with an ongoing felid conservation project in northern California, USA. Their system connected to the camera trap at pre-determined intervals to download, classify images within identified events, and send data on identified target species. To conserve battery power, the authors opted to only send the image metadata and classification data rather than sending the entire image (Tulasi et al. 2023). Whytock et al. (2023) combined edge-AI with a camera trap to classify images and send real-time alerts of wildlife detections over the Iridium satellite network in a region of Africa that lacked a cellular network. Similar to Tulasi et al. (2023), notifications consisted of the image metadata and classification to increase efficiency and reduce the high cost of data transfer over a satellite network. Whytock et al. (2023) discussed the potential for the quantity of transmitted data to become overwhelming, even with automated image classification. The authors suggested reducing the amount of data sent in real-time by adapting methodology to send data about events (i.e., the same individual/species captured in multiple images) rather than sending data on singular images.

CHAPTER THREE

STUDY 1: UNCONNECTED CAMERA TRAP PERFORMANCE

Introduction

Assessments of wildlife populations and their distribution inform wildlife research and management decisions. For example, wildlife surveys are used to set harvest objectives for game species, assess the effectiveness of management interventions, and evaluate population size and distribution of wildlife species (Rabe et al. 2002, Meek et al. 2012). Inaccurate survey estimates could contribute to poor management decisions that may harm wildlife populations, contribute to habitat degradation, or promulgate conflict among stakeholders such as sportsmen, landowners, conservationists, and other wildlife enthusiasts.

Camera trapping is a widely accepted, non-invasive method for surveying wildlife populations that requires considerably less field effort than other methods and is particularly advantageous when studying reclusive or low-density populations (Karanth and Nichols 1998, Cutler and Swann 1999, Tobler et al. 2008, Kays et al. 2009, Burton et al. 2015). However, several variables must be considered when designing camera trap surveys to avoid biasing population estimates, including differences in performance among camera trap models and differences in environmental conditions among camera trap sites within the survey (Hofmeester et al. 2019).

Most contemporary camera traps use passive infrared (PIR) sensors that monitor infrared radiation (e.g., thermal energy) emitted from the surface of objects within the camera trap's detection zone. A camera trap triggers when a change in energy (increase or decrease) is detected by the PIR sensor relative to the background surface (Welbourne et al. 2016). However, factors such as the sensitivity of PIR sensors (i.e., threshold of thermal difference that results in the camera trap triggering), the size of camera trap detection zones, and trigger speeds (i.e., the time interval between a PIR sensor detecting a thermal anomaly and the camera triggering), all vary among camera trap models (Swann et al. 2004, Wellington et al. 2014, Rovero and Zimmermann 2016). Different camera trap specifications provide different advantages depending on the goals of a particular monitoring effort, but if multiple camera trap models are used in one survey, variability in detection rates caused by differences in camera trap function must be accounted for during data analyses (Swann et al. 2004, Damm et al. 2010, Wellington et al. 2014, Burton et al. 2015, Hofmeester et al. 2019, Greco and Rovero 2021).

Differences in camera trap function may also interact with the environmental conditions at a given camera trap site, affecting overall camera trap performance (Swann et al. 2004, Newey et al. 2015). Warmer air temperatures may reduce camera trap detection probabilities by decreasing the temperature differential between the background surface and the surface temperature of an animal (Swann et al. 2004, Jacobs and Ausband 2018). Moll et al. (2020) observed that increasing vegetation obstruction decreased detection rates for some species. Rowcliffe et al. (2011) reported shorter camera trap detection distances during the rainy season in Panama, with detection distances as much as 70% shorter as compared to the dry season. The effects of other environmental conditions – such as cloud cover or wind speed – on the detection rates of camera traps have not been adequately evaluated, but similar weather impacts have been documented in other wildlife survey methods that employ thermal sensors in similar fashion as PIR sensors (Havens and Sharp 2015).

One frequently discussed drawback to camera trapping is that camera traps can generate thousands of images that must be analyzed (Swanson et al. 2015). This process is time-consuming and can significantly delay subsequent data analyses (Newey et al. 2015). Delays in analysis can be exacerbated if the camera traps produce large numbers of false positive images, that is, when the camera trap captures a “blank” image with no animal in it. False positive images waste battery power and memory on the camera trap’s SD card and increase the amount of time needed to process data. Solutions to limit false positives include adjusting the camera trap orientation to face north or north-east (Hughson et al. 2010) and clearing dense vegetation from the camera trap’s field of view (Zimmermann and Rovero 2016). However, these solutions are not practical in every situation, and additional means of reducing false positive triggers would advance camera trapping technology.

The Grizzly Systems camera trap (Grizzly Systems, Bozeman, MT) is a new and untested camera trap model that features edge artificial intelligence (AI) technology designed to limit the capture of false positive images. The term “edge-AI” reflects that the camera trap itself uses artificial intelligence to analyze a thermal anomaly rather than offloading data to be analyzed elsewhere. This “smart camera” uses a quad-element PIR sensor, with an ultra-low power AI trigger. This specialized trigger analyzes thermal anomalies detected by the PIR sensor before triggering to capture an image, thus filtering out false positive triggers (e.g., moving vegetation on a windy day) which saves battery life, SD card storage capacity, and the time and effort needed to analyze camera trap images.

Objectives

I compared the performance of the edge-AI enabled Grizzly Systems camera trap with 2 traditional, commercially available camera traps (without edge-AI): the Browning Strike Force APEX (Prometheus Group LLC, Birmingham, AL), and the Reconyx Hyperfire 2 (Reconyx, Inc., Holmen, WI). The Browning camera trap is relatively inexpensive, and is commonly used by wildlife managers (e.g., Palencia et al. 2023). The Reconyx camera trap is a high-performance camera trap that is commonly used by wildlife researchers (e.g., Monterroso et al. 2020, Jessop et al. 2021). Camera trap performance was evaluated by measuring rates of positive detections, false positives, missed detections, and correct actions (Table 1). Additionally, I assessed the effects of 5 environmental variables (air temperature, relative humidity, wind speed, cloud cover, and vegetation type) on camera trap performance (Table 2).

Table 1. Camera trap responses used to evaluate the performance of 3 camera trap models tested during summer 2023 in south-central Montana, USA.

Camera Trap Responses	Definition
Positive Detection	Animal present and image captured.
Missed Detection	Animal present but no image captured. Determined when ≥ 1 camera trap in group captured positive detection.
False Positive	No animal present but camera trap triggered and captured blank image.
Correct Action	Aggregate variable quantifying camera trap efficiency. Determined if camera trap either 1) captured positive detection OR 2) did not capture false positive when ≥ 1 camera trap in group captured a false positive image.

Table 2. Predictor variables included in the performance assessment of 3 camera trap models tested during summer 2023 in south-central Montana, USA.

Variable	Definition
Camera Trap Model	3 camera trap models were tested: Grizzly Systems (AI-enabled), Browning, Reconyx.
Temperature	Degrees Celsius. Recorded every 10 minutes at each camera trap site.
Wind Speed	Kilometers per hour. Recorded every 10 minutes at each camera trap site.
Relative Humidity	Percent. Recorded every 10 minutes at each camera trap site.
Cloud Cover	Percent. Hourly estimate over the study area using the GOES satellite network.
Vegetation Type	Classified as grassland or forest at each camera trap site based on the camera trap field of view.

I expected the Grizzly Systems camera trap equipped with the edge-AI PIR sensor, to capture fewer false positive images than the Browning or Reconyx camera traps. I anticipated that increases in air temperature or wind speed would decrease positive detections and increase false positives for the Reconyx and Browning camera traps, due to their effects on the background surfaces in the camera traps' detection zone, but less so for the Grizzly Systems camera trap because of its edge-AI technology. I hypothesized that cloud cover would increase the probability of positive detections for all 3 camera traps by making detection zones more homogenous, thus making thermal anomalies (i.e., animal movement) more distinct. Similarly, I expected increased cloud cover to decrease the rate of false positives by reducing heterogeneity in the detection zone. As relative humidity increased, I hypothesized that positive detections would decrease due to humidity's interference with emissions of infrared energy and the potential to obscure the temperature differential between the background surface and an animal passing through the camera trap's detection zone. I also expected that camera traps located in forest cover types would have fewer positive detections, more false positives, and more missed detections than camera traps located in grassland cover types due to greater vegetative heterogeneity and greater viewshed obstruction in forested sites.

Study Area

My study was conducted at mid-elevation sites (circa 2,000 m) about 40 km southwest of Emigrant, MT, north of Yellowstone National Park (YNP) within the Northern Yellowstone Range (NYR), and within the northern extent of the Greater Yellowstone Ecosystem (GYE; Mosley et al. 2018). Outside of YNP, the NYR is a working landscape comprised of multiple-use federal and state lands, ranches, and other private lands that provide critical winter and summer habitat for wildlife (Mosley et al. 2018). Eight species of wild ungulates inhabit the NYR: bison (*Bison bison*), Rocky Mountain elk (*Cervus elaphus nelsoni*), Rocky Mountain mule deer (*Odocoileus hemionus hemionus*), white-tailed deer (*O. virginianus canadensis*), moose (*Alces alces*), pronghorn (*Antilocapra americana*), Rocky Mountain bighorn sheep (*Ovis canadensis canadensis*), and mountain goats (*Oreamnos americanus*). Domestic ungulates cohabit portions of the NYR, including cattle (*Bos taurus*), sheep (*Ovis airies*), and horses (*Equus caballus*), and several species of ungulate predators also cohabit the NYR [grizzly bears (*Ursus arctos horribilis*), black bears (*Ursus americanus*), coyotes (*Canis latrans*), mountain lions (*Puma concolor*), and wolves (*C. lupus*)] (Mosley and Mundinger 2018). Vegetation generally consists of irrigated pastures and hayfields at low elevations, foothill grasslands and sagebrush steppe at mid-elevations, and conifer forests at mid- to higher elevations. Dominant native plant species include bluebunch wheatgrass (*Pseudoroegneria spicata*), Idaho fescue (*Festuca idahoensis*), Columbia needlegrass (*Stipa nelsoni*), mountain big sagebrush (*Artemisia tridentata* ssp. *Vaseyana*), lodgepole pine (*Pinus contorta*), and Douglas-fir (*Pseudotsuga menziesii*; Pfister et al. 1977, Mueggler and Stewart 1980).

Methods

I compared the performance of the 3 camera trap models in a field setting using methods similar to Jacobs and Ausband (2018). A camera trap group consisted of one camera trap of each model (Browning, Reconyx, and Grizzly Systems) mounted side by side (Figure 1). Placement of specific camera trap models was randomized to minimize bias caused by differences in the camera trap field of view (Wellington et al., 2014). I mounted camera trap groups to trees, wooden fence posts, or steel t-posts approximately 75 cm from ground level to optimize the detection of large animals, specifically elk, grizzly bears, and wolves.

Figure 1. Illustration of a camera trap group equipped with weather meters and exclosure fencing during testing in south-central Montana, USA. Camera models from left to right are: Reconyx, Browning, Grizzly Systems.

Ten camera trap groups were deployed for a field test from 15 June–15 September 2023. I placed camera trap groups using feature-based site placement to maximize camera trap exposure to wildlife (e.g., creek crossings, game trails, etc.; Iannarilli et al. 2021). Site selection was restricted to private property to reduce the risk of theft. Camera trap sites were located at least 100 m apart. All camera traps were set to high sensitivity and to capture one image per trigger, with a 3-second (Grizzly Systems) or 5-second delay between triggers (Browning and Reconyx). The delay on the Grizzly Systems' camera trap was not adjustable, and the shortest delay possible for Browning and Reconyx camera traps was 5 seconds. I installed a woven wire exclosure around each camera trap group to prevent damage from wildlife or livestock, and I cleared low-hanging branches and dense vegetation within 1 m of the camera traps upon initial deployment and as needed throughout the study. I visited camera trap sites weekly to exchange SD cards and monitor battery levels.

All images of humans and vehicles were deleted prior to data analysis. Images within 5 minutes before and after camera trap checks and when one or more camera traps in a group were non-functioning were also removed from analysis. I excluded data from two camera trap sites due to excessive equipment malfunctions.

Image metadata was modified using ExifTool software to reflect the start time of the camera trap group (Exiftool version 12.41, exiftool.org, accessed 17 Jul 2022). This standardized the timestamp associated with each image and accounted for occasions when the date and time was set incorrectly or when clocks within a camera trap group were not set to the same time. Images from each camera trap were then renamed using a modified version of the Image Renamer R script (Wildlife Coexistence Lab, github.com/WildCoLab, accessed 17 Jul 2023).

This gave each image a unique label that contained the camera trap ID and the image timestamp. I used Timelapse2 software (Greenberg et al. 2019) to manually annotate all images and record blank images and positive detections.

The 3 camera trap models took images at different rates, which did not allow for direct comparison of individual images among the camera traps in a group. Instead, images were aggregated into 2-minute event bins. For each bin, if a camera trap captured an image of an animal, it was classified as a positive detection. If a camera trap captured a blank image (i.e., no animal in the image) and there were no positive detections in the event, it was classified as a false positive. If 1 camera trap in the group captured a positive detection, but 1 or more of the other camera traps captured a blank image or did not take an image during the same event bin, it was classified as a missed detection. Finally, I combined positive detections, missed detections, and false positives into a fourth variable called "correct actions". Correct actions occurred whenever a camera trap did what it was expected to do—either capture a positive detection when an animal was present or not capture a false positive image when no animal was present.

<u>Environmental Covariates</u>

I measured 5 environmental covariates to evaluate their effects on camera trap performance: vegetation type (forest, grassland), air temperature (°C), relative humidity (%), wind speed (km/h), and cloud cover (%). I selected environmental covariates based on their ease of measurement and interpretability, relevance to their effect on thermal reflectance within the detection zone, and merit as determined by previous studies on the performance of camera traps or similar thermal sensors. The vegetation type at each camera trap site was classified as either grassland (n=4) or forest (n=4) based on the predominant vegetation within the field of view of the camera trap group. Weather variables were monitored at each camera trap site using a Kestrel 5500 weather meter (Nielsen-Kellerman, Boothwyn, PA). Weather measurements were recorded every 10 minutes and data was downloaded from the camera trap sites approximately every 2 weeks. Satellite estimates of cloud cover were collected from the GOES-East Day Night Cloud Micro Combo product and processed using Google Earth Engine and McIDAS-V to generate an hourly estimate of the proportion of cloud cover over the study area (Achtor et al. 2008, Cavazzani et al. 2020).

Data Analysis

I used generalized linear mixed models with a binomial error distribution and logit-link function (Hosmer and Lemeshow 2000) to evaluate the effect of camera trap model and environmental conditions on 4 response variables: positive detections, false positives, missed detections, and correct actions. Covariates included camera trap model, air temperature, relative humidity, wind speed, cloud cover, and vegetation type.

Before developing my candidate models, I tested my weather variables for multicollinearity by calculating pairwise Spearman's rank correlations. If correlation was detected between a pair of predictor variables ($|r| > 0.70$; Green 1979), I retained the variable that contributed most to interpretation of camera trap performance and eliminated the other variable from analyses (Hosmer and Lemeshow 2000). I detected correlation between relative humidity and temperature ($|r| = 0.86$) and eliminated relative humidity from the analysis. The correlation between all other variables was < 0.70.

I developed a set of 26 candidate models based on my a priori hypotheses about the effects of environmental conditions on camera trap performance (Table 3; Burnham and

Anderson 2002). The Grizzly Systems camera trap was the reference category, and individual camera trap ID was included as a random effect to account for repeated observations from the camera trap and to limit Type I error. Measures of environmental variables were standardized prior to modeling to improve model convergence (Schielzeth 2010). Results are presented using unscaled values.

Table 3. Candidate model set for the effects of camera trap model and environmental conditions on positive detections, false positives, missed detections, and correct actions among 3 camera trap models evaluated in south-central Montana, USA during summer 2023.

Model	**Description**
Null	Null model
Model 1	Camera trap model
Model 2	Temperature
Model 3	Wind speed
Model 4	Cloud cover
Model 5	Vegetation type
Model 6	Temperature + wind speed + temperature × wind speed
Model 7	Temperature + cloud cover + temperature × cloud cover
Model 8	Temperature + vegetation type + temperature × vegetation type
Model 9	Wind speed + cloud cover + wind speed × cloud cover
Model 10	Wind speed + vegetation type + wind speed × vegetation type
Model 11	Cloud cover + vegetation type + cloud cover × vegetation type
Model 12	Camera trap model + temperature
Model 13	Camera trap model + wind speed
Model 14	Camera trap model + cloud cover
Model 15	Camera trap model + vegetation type
Model 16	Camera trap model + temperature + wind speed + cloud cover + vegetation type
Model 17	Camera trap model + temperature + camera trap model × temperature
Model 18	Camera trap model + wind speed + camera trap model × wind speed
Model 19	Camera trap model + cloud cover + camera trap model × cloud cover
Model 20	Camera trap model + vegetation type + camera trap model × vegetation type
Model 21	Camera trap model + temperature + wind speed + temperature × wind speed
Model 22	Camera trap model + temperature + cloud cover + temperature × cloud cover
Model 23	Camera trap model + temperature + vegetation type + temperature × vegetation type
Model 24	Camera trap model + wind speed + cloud cover + wind speed × cloud cover
Model 25	Camera trap model + wind speed + vegetation type + wind speed × vegetation type
Model 26	Camera trap model + cloud cover + vegetation type + cloud cover × vegetation type

I assessed the strength of evidence for each candidate model with Akaike's Information Criterion adjusted for small sample size (AIC_c), and I ranked all models by calculating Δ AIC_c (Δ_i), the difference in AIC_c between the lowest-AIC_c model and AIC_c for each candidate model. Per Burnham and Anderson (2002), I considered the model with the lowest AIC_c value to be the model that best explained camera trap performance. For each parameter estimate in the top-ranked model, I calculated odds ratios (Hosmer and Lemeshow, 2000) and 85% CI (Arnold 2010). If the 85% CI of any parameter coefficient overlapped zero, these covariates were considered uninformative, and I concluded they did not have any substantive effect on the response variable (Arnold 2010). Similarly, if the 85% CI of an odds ratio overlapped 1, I concluded that the covariate had limited influence on the response variable (Hosmer and Lemeshow 2000). Visualizations for the top-ranked candidate models were created using the ggeffects package (Lüdecke 2018). When applicable, non-focal variables were held at their means. All analyses were performed in R (Program R, version 4.3.1, Foundation for Statistical Computing, Vienna, Austria)

Results

My analysis included 8,614 2-minute event bins, encompassing 49,859 images over 547 camera trap group nights at 8 sites ($\bar{X}$ = 68.4 nights per site). Across all 3 camera trap models, there were 6,565 positive detections, 5,653 false positives, 3,239 missed detections, and 16,968 correct actions (Figure 2). The average temperature across the camera trap sites was 21.6° C, the average wind speed was 3.1 km/h, and the average cloud cover was 17.4%.

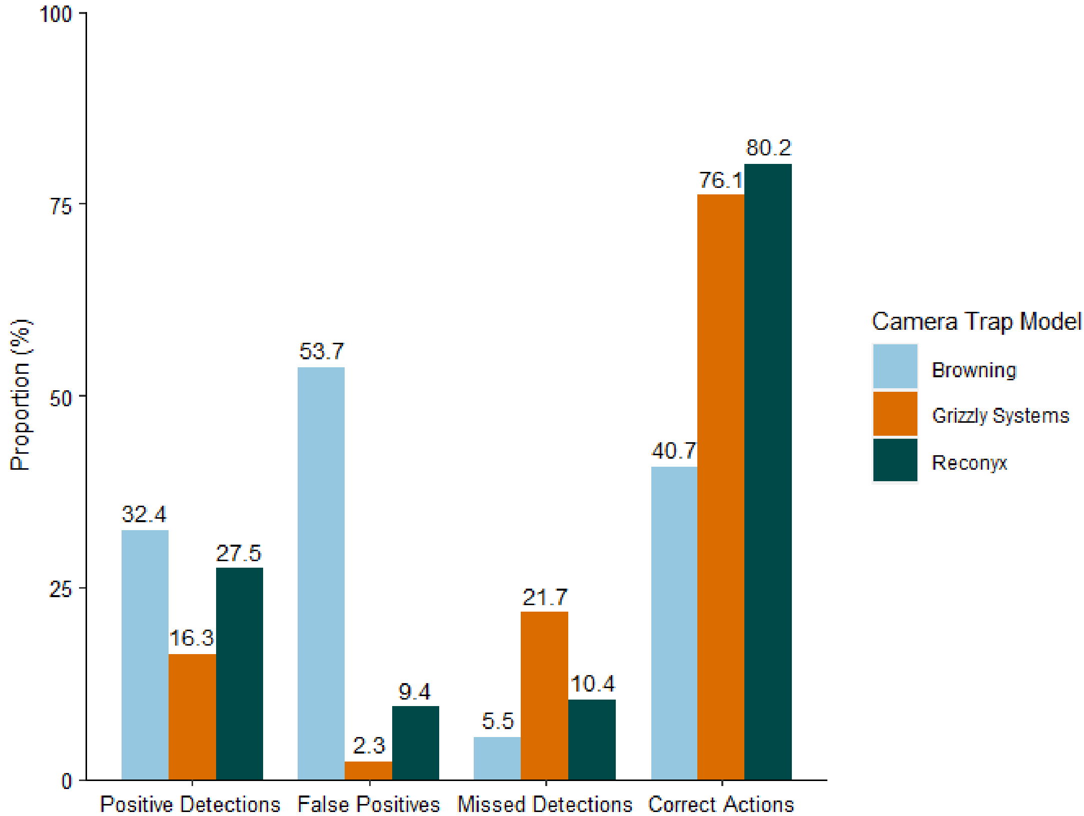

Figure 2. Proportion of events (n = 8,614 events) for the response variables of positive detections, false positives, missed detections, and correct actions among 3 camera trap models tested in south-central Montana, USA during summer 2023.

<u>Camera Trap Performance</u>

Of the 26 candidate models that I evaluated, only one candidate model received support for each of the 4 response variables. The candidate model containing camera trap model, temperature, wind speed, and the interaction of temperature and wind speed received the most support for positive detections (Δ $AIC_c = 0$ and $w_i = 0.96$; Table 4). The candidate model containing camera trap model, temperature, and the interaction between camera trap model and temperature received the most support for the response variables of false positives, missed detections and correct actions (Δ $AIC_c = 0$ and $w_i = 1$; Table 4).

Table 4. Fit statistics for the top 3 candidate models evaluating camera trap models and environmental effects on the probability of positive detections, false positives, missed detections, and correct actions. Models are ranked by Akaike Information Criterion (AIC_c), K is the number of fixed effects, Δ AIC_c is the difference of each model's AIC_c value from that of the highest ranked model, and w_i is the Akaike weight (sum of all Akaike weights = 1.00).

Model	**K[1]**	**AIC_c**	**Δ AIC_c**	**w_i**	**Cumulative w_i**
Positive Detections					
Camera trap model + temperature + wind speed + temperature × wind speed	7	20457.12	0	0.96	0.96
Temperature + wind speed + temperature × wind speed	5	20463.70	6.58	0.04	1.00
Camera type + temperature + wind speed + cloud scale + vegetation type	8	20716.27	259.15	0	1.00
Null	2	24502.10	4044.98	0	1.00
False Positives					
Camera trap model + temperature + camera trap model × temperature	7	12916.61	0	1	1.00
Camera trap model + temperature + vegetation type + temperature × vegetation type	7	13581.64	665.03	0	1.00
Temperature + vegetation type + temperature × vegetation type	5	13597.67	681.06	0	1.00
Null	2	15572.60	2655.99	0	1.00
Missed Detections					
Camera trap model + temperature + camera trap model × temperature	7	10194.77	0	1	1.00
Camera trap model + temperature + wind speed + temperature × wind speed	7	10223.81	29.04	0	1.00
Camera trap model + temperature	5	10224.80	30.02	0	1.00
Null	2	10263.26	68.49	0	1.00

Table 4 continued.

Model	**K[1]**	**AIC_c**	**$\Delta\ AIC_c$**	**w_i**	**Cumulative w_i**
Correct Actions					
Camera trap model + temperature + camera trap model × temperature	7	23142.80	0	1	1.00
Camera trap model + wind speed + camera trap model × wind speed	7	24813.05	1670.25	0	1.00
Camera trap model + cloud cover + camera trap model × cloud cover	7	25104.77	1961.97	0	1.00
Null	2	25469.54	2326.73	0	1.00

[1] All models included random intercepts for individual camera traps.

The probabilities of all 4 responses (positive detections, false positives, missed detections, correct actions) varied among camera trap models. Browning and Reconyx camera traps were 5 and 2.75 times more likely to capture positive detections than Grizzly Systems, respectively (Table 5). Browning was 99 times more likely to capture false positives images than Grizzly Systems, while Reconyx was 6 times more likely to capture false positives compared to Grizzly Systems (Table 5). The probability of missed detections was 93% and 73% less for Browning and Reconyx compared to Grizzly Systems, respectively (Table 5). Finally, the probability of obtaining correct actions was 82% less for Browning than Grizzly Systems, but the probability of correct actions did not differ between Grizzly Systems and Reconyx (Table 5).

Environmental Effects

Air temperature influenced the probabilities of all 4 responses (positive detections, false positives, missed detections, correct actions), with wind speed also influencing the probability of positive detections (Table 5). In contrast, neither cloud cover nor vegetation type had substantive effects on any of the 4 response variables.

The probability of positive detections decreased for all 3 camera trap models as air temperature and wind speed increased, especially when air temperature exceeded 5°C and wind speed exceeded 5 km/h (Table 5; Figure 3). However, the negative effect of wind speed on the probability of positive detection was moderated by low air temperature. Even at wind speeds ≥ 25 km/h, the probability of detection did not begin to decrease until air temperatures reached ≥ 10°C (Figure 4).

Table 5. Model coefficients (β), standard errors (SE), odds ratios, and 85% confidence intervals (CIs) of the top-ranked models for positive detections, false positives, missed detections, and correct actions. “Browning” and “Reconyx” were indicator variables of the nominal variable “camera trap model”. The Grizzly Systems camera trap model was the reference category.

			85% CI (β)			85% CI (Odds ratio)	
Predictor Variable	**β**	**SE**	**Lower**	**Upper**	**Odds ratio**	**Lower**	**Upper**
Positive Detections							
Grizzly Systems (intercept)	-2.55	0.30	-2.99	-2.11	---	---	---
Browning	1.62	0.46	0.96	2.29	5.07	2.60	9.86
Reconyx	1.01	0.45	0.36	1.66	2.75	1.44	5.26
Temperature	-1.28	0.03	-1.32	-1.24	0.28	0.27	0.29
Wind speed	-0.46	0.03	-0.50	-0.42	0.63	0.61	0.66
Temperature × wind speed	-0.55	0.04	-0.60	-0.50	0.58	0.55	0.61
False Positives							
Grizzly Systems (intercept)	-4.62	0.42	-5.23	-4.01	---	---	---
Browning	4.60	0.63	3.70	5.50	99.51	40.32	245.58
Reconyx	1.86	0.61	0.98	2.74	6.42	2.68	15.42
Temperature	-1.02	0.09	-1.15	-0.89	0.36	0.32	0.41
Browning × temperature	2.66	0.10	2.52	2.80	14.25	12.38	16.40
Reconyx × temperature	1.52	0.10	1.37	1.66	4.56	3.94	5.27
Missed Detections							
Grizzly Systems (intercept)	0.63	0.24	0.28	0.98	---	---	---
Browning	-2.62	0.37	-3.15	-2.09	0.07	0.04	0.12
Reconyx	-1.52	0.36	-2.04	-1.00	0.22	0.13	0.37
Temperature	0.31	0.05	0.24	0.39	1.37	1.27	1.47
Browning × temperature	-0.49	0.08	-0.61	-0.37	0.62	0.55	0.69
Reconyx × temperature	-0.17	0.07	-0.28	-0.06	0.85	0.76	0.94

Table 5 continued.

Predictor Variable	β	SE	85% CI (β) Lower	85% CI (β) Upper	Odds ratio	85% CI (Odds ratio) Lower	85% CI (Odds ratio) Upper
Correct Actions							
Grizzly Systems (intercept)	1.42	0.26	1.05	1.79	---	---	---
Browning	-1.74	0.39	-2.31	-1.17	0.18	0.10	0.31
Reconyx	0.15	0.38	-0.40	0.70	1.17	0.67	2.02
Temperature	0.95	0.03	0.90	1.00	2.58	2.46	2.71
Browning × temperature	-2.09	0.05	-2.16	-2.02	0.12	0.11	0.13
Reconyx × temperature	-0.74	0.05	-0.81	-0.67	0.48	0.45	0.51

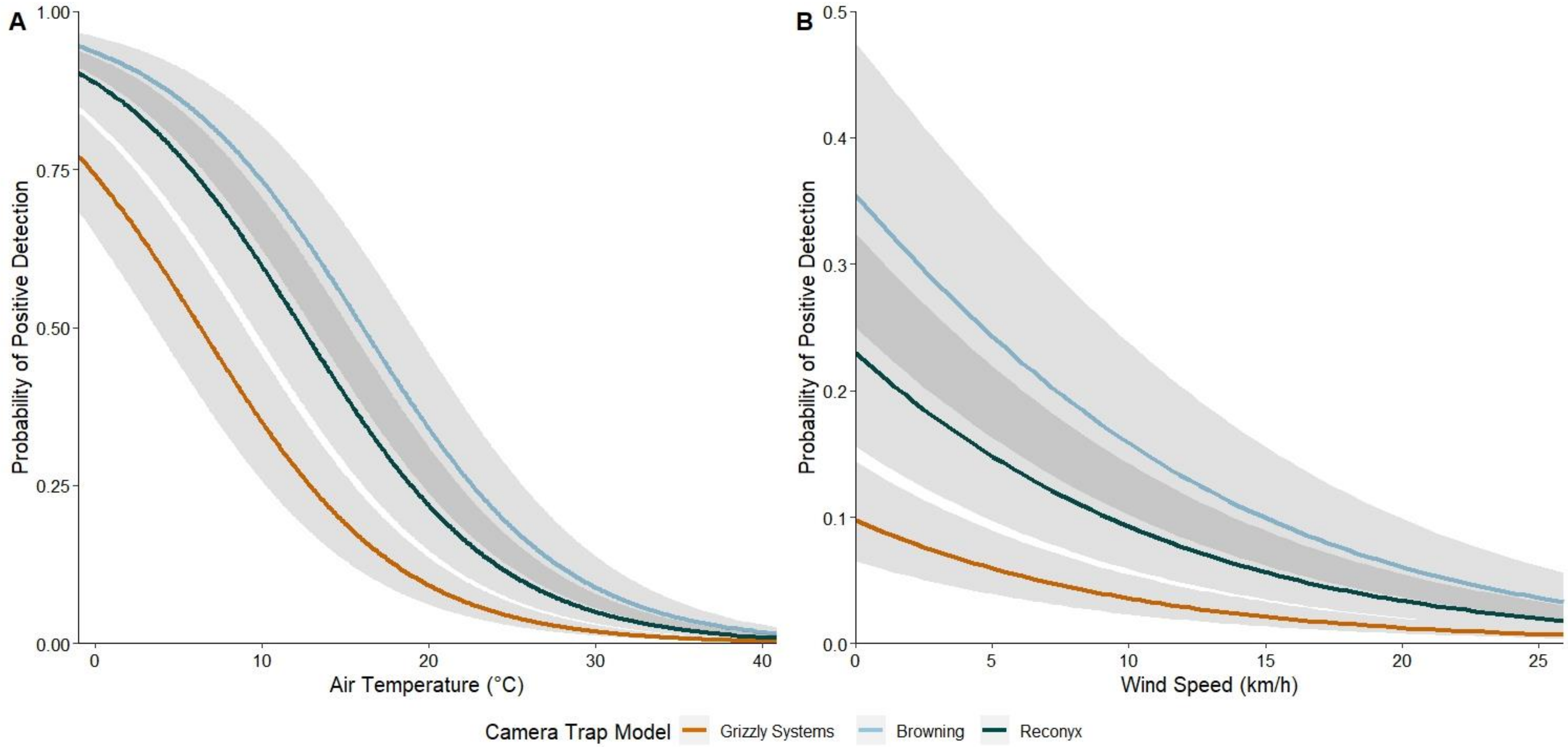

Figure 3. Predicted probability of positive detections among 3 camera trap models in south-central Montana, USA during summer 2023. Responses by camera trap models are shown relative to air temperature (A) and wind speed (B). Shaded areas represent 85% confidence intervals.

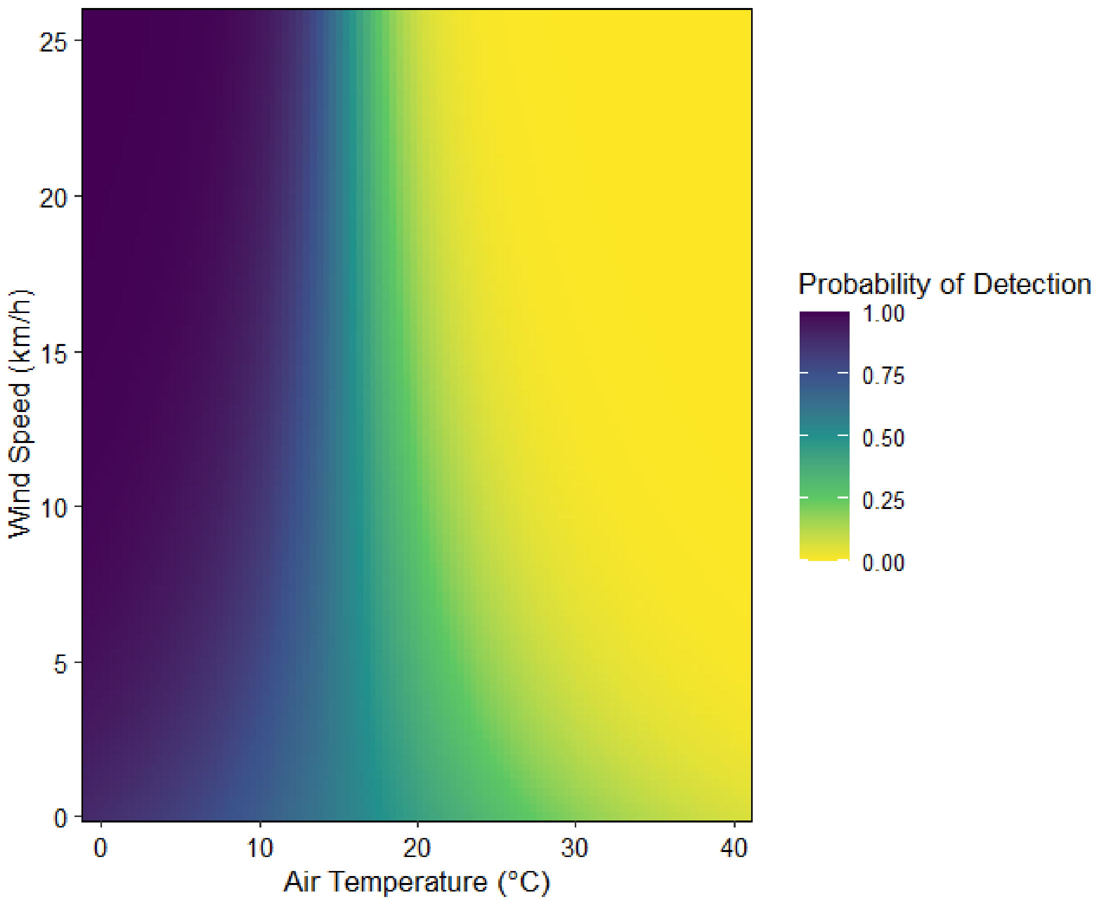

Figure 4. Heat map showing the predicted probability of positive detections for 3 camera trap models relative to temperature and wind speed in south-central Montana, USA during summer 2023.

The influence of air temperature on the probability of false positives varied among camera trap models (Table 5; Figure 5). Increased air temperatures increased the probability of false positives for both Browning and Reconyx. As air temperature increased, Browning and Reconyx were 5.13 times and 1.64 times more likely, respectively, to capture false positives. The probability of the Browning camera trap capturing false positives increased substantially when air temperature exceeded 10° C (Figure 5). In contrast, the probability that Grizzly Systems camera traps captured false positives decreased slightly as air temperature increased (Table 5; Figure 5).

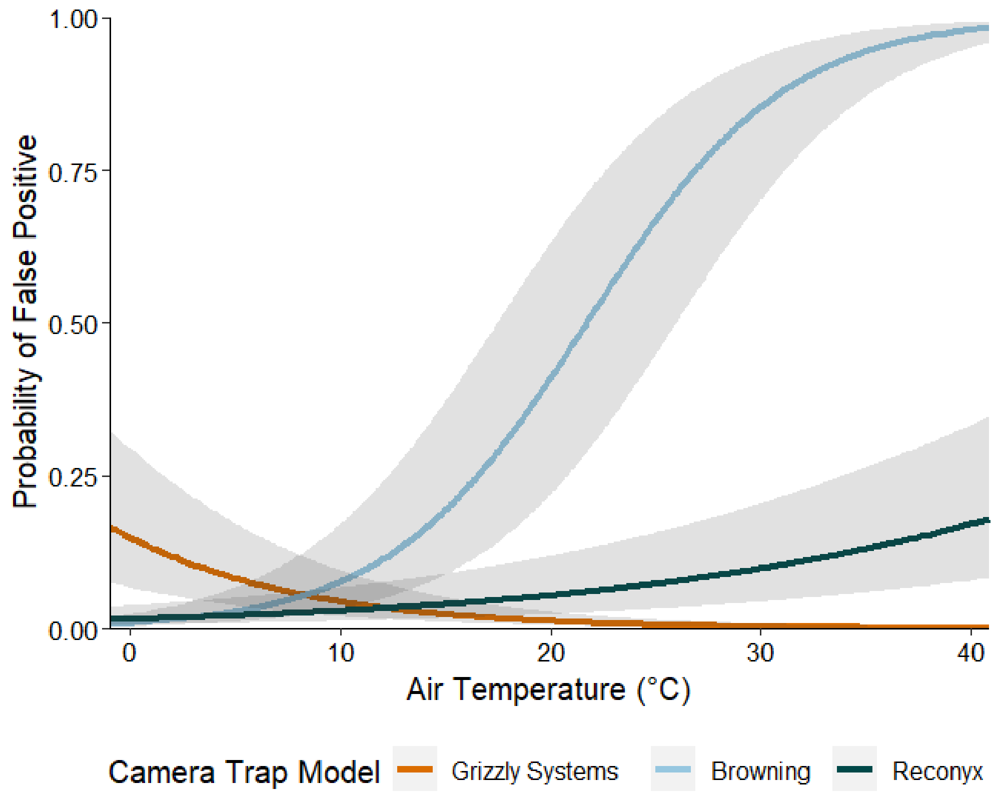

Figure 5. Predicted probability of false positives among 3 camera trap models in south-central Montana, USA during summer 2023. Responses by camera trap models are shown relative to air temperature. Shaded areas represent 85% confidence intervals.

The probability of missed detections varied for all 3 camera trap models as air temperature increased (Table 5; Figure 6). Missed detections increased markedly with increasing air temperatures for the Grizzly Systems camera trap, but less so for the Reconyx camera trap. However, the probability of missed detections decreased for the Browning camera trap as temperatures increased (Figure 6). The Browning camera trap was 16% less likely to miss detections as air temperature increased, whereas the Reconyx camera trap was 16% more likely to miss detections as air temperature increased (Table 5).

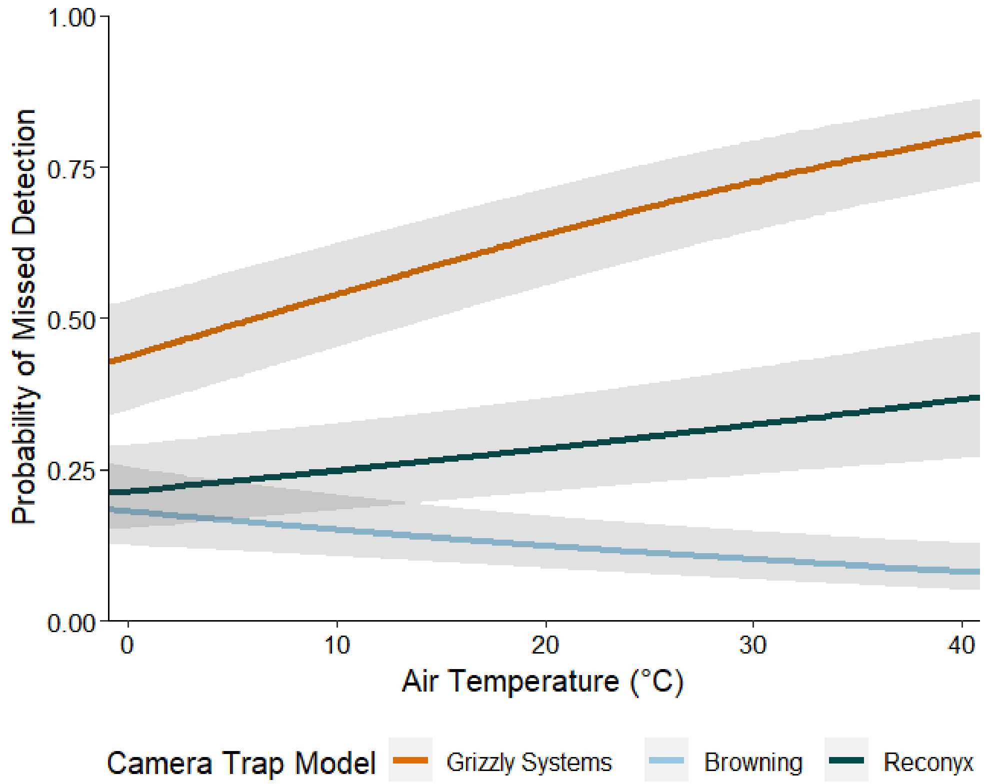

Figure 6. Predicted probability of missed detections among 3 camera trap models in south-central Montana, USA during summer 2023. Responses by camera trap models are shown relative to air temperature. Shaded areas represent 85% confidence intervals.

The influence of air temperature on the probability of correct actions also varied among camera trap models. The probability of the Browning camera trap performing correct actions decreased precipitously as air temperature increased, whereas the Grizzly Systems camera trap was much more likely to perform correct actions when temperatures were warmer (Figure 7). As air temperature increased, the Browning camera trap was 69% less likely to provide correct actions, and the Reconyx camera trap was 23% more likely to provide a correct action (Table 5; Figure 7).

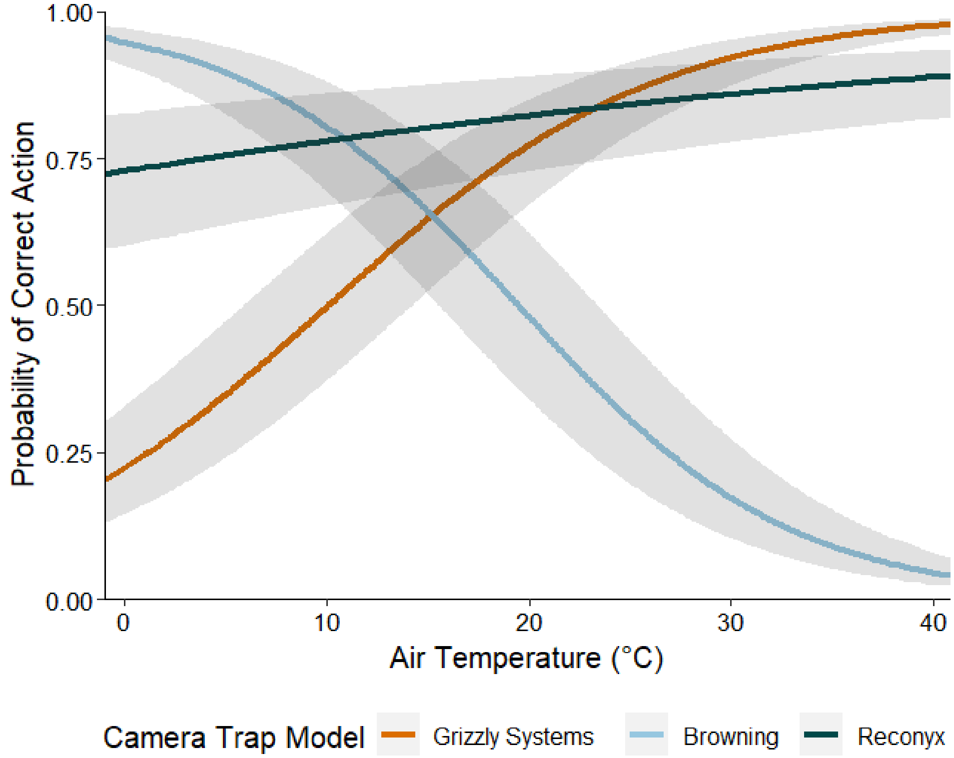

Figure 7. Predicted probability of correct actions among 3 camera trap models in south-central Montana, USA during summer 2023. Responses by camera trap models are shown relative to air temperature. Shaded areas represent 85% confidence intervals.

Discussion

Camera Trap Performance

As predicted, the edge AI-enabled Grizzly Systems camera trap was less likely to capture false positive images than the Browning or Reconyx camera traps. This result was achieved even though the Grizzly Systems camera trap had a wider detection zone than either the Browning or Reconyx camera traps (detection angle of 55° vs. 42.2° and 45.2°, respectively). Previous research has documented that camera traps with wider detection zones are more likely to capture false positives (Swann et al. 2004).

I did not find support for my prediction that the Grizzly Systems, Browning, and Reconyx camera traps would have similar probabilities of positive detections and missed detections. Reconyx and Browning captured more positive detections and had fewer missed detections than Grizzly Systems. Similar to my results, Swearingen et al. (2023) observed no differences in the number of positive detections among camera traps manufactured by Browning and Reconyx in mixed woodland and upland prairie of west-central Illinois. Finally, in my study, the probability of providing correct actions was much less for Browning than either Reconyx or Grizzly Systems. Other previous studies evaluating the performance of Browning or Reconyx camera trap models have produced mixed results, sometimes concluding that Browning or Reconyx camera traps performed better or worse than other camera trap models (Swann et al. 2014, Greco and Rovero 2021, Palencia et al. 2022). To the best of my knowledge, my study is the first to document the performance of a camera trap that incorporates edge-AI within its PIR sensor.

Environmental Effects

Consistent with my hypothesis, increased air temperatures reduced the probability of positive detections across all 3 camera trap models. Warmer air temperatures increase the emission of thermal energy from the surfaces of objects within the camera trap's detection zone, which potentially decreases the temperature differential between background surfaces and animal surfaces, thereby reducing the likelihood that camera traps will trigger (Swann et al. 2004, Welbourne et al. 2016, Jacobs and Ausband 2018). Swann et al. (2004) observed that PIR sensors were less sensitive at air temperatures of 31 to 36° C. Similarly, my results indicated that positive detections were unlikely to occur when air temperature was 30 to 40° C. In my study, I also attribute the low probabilities of positive detections when air temperatures were high to (1) animals were likely more sedentary and therefore more difficult to detect when air temperature was ≥ 30° C, and (2) relatively few events occurred when air temperature at my camera trap sites was ≥ 30° C (Jacobs and Ausband 2018). Among the 6,565 positive detections in my study, only 106 (1.6 %) were captured when air temperature was ≥ 30° C.

The influence of air temperature on false positive detection probabilities was inconsistent among camera trap models. As expected, warmer air temperatures increased the likelihood that Browning camera traps would capture false positives, but this effect was much less pronounced in Reconyx camera traps. An unexpected result was that Grizzly Systems camera traps were somewhat less likely to capture false positives as air temperature increased. My data suggests that the Grizzly Systems edge AI-enabled PIR sensor successfully analyzed thermal anomalies to prevent false positive triggers, even when temperatures were warm.

The Grizzly Systems and Reconyx camera traps had a much higher rate of correct actions than the Browning camera trap, particularly as air temperatures increased. The probability of correct actions reflects the overall efficiency of a camera trap, by balancing positive detections and false positives. Camera trap efficiency is not frequently discussed in scientific literature beyond reporting overall sums of positive and false positive detections or when discussing the use of machine learning to automate image classification (Greco and Rovero 2021, Fennell et al. 2022). This may be caused by scientists’ desire to obtain as many positive detections as possible, or maybe due to researchers having sufficient resources to address the burden of false positive images (e.g., technical knowledge to apply machine learning techniques to filter out blank images, financial resources for manual annotation of images, etc.) compared to practitioners using camera traps to inform site-specific wildlife management decisions.

Increased wind speed decreased the detection probability of positive detections, but wind speed did not affect the probability of false positives, missed detections, or correct actions, regardless of camera trap model. When camera traps were located in tree canopies in south-central Peru, Gregory et al. (2014) attributed a high rate of false positives to wind causing vegetation to move within a camera trap's detection zone, but wind speed was not measured.

I expected increased cloud cover would shield the detection zone from solar radiation, thereby creating a more homogenous background that would increase the probability of positive detections and decrease the probability of false positives (Havens and Sharp 2015). For example, overcast skies enhanced the detection of bighorn sheep in aerial surveys using forward-looking infrared imagery (Bernatas and Nelson 2004). However, cloud cover in my study did not affect the probability of positive detections, false positives, missed detections, or correct actions. Thermal imagers used for wildlife surveys such as in Bernatas and Nelson (2004) are often at greater distances to wildlife than a PIR sensor within a camera trap (600 m vs. > 40 m), and therefore likely more sensitive to thermal heterogeneity compared to the PIR sensor of a camera trap.

I also expected that a vegetation type with greater structural heterogeneity and greater viewshed obstruction (e.g., forest vs. grassland) would decrease positive detection probability. In contrast, vegetation type in my study did not influence positive detections nor the probabilities of false positives, missed detections, or correct actions. This differs from the results of Moll et al. (2020), who documented that greater vegetation obstruction decreased positive detections of some wildlife species. I presume that my results differed because the forest and grassland vegetation types in semi-arid south-central Montana, USA likely had much less vegetative cover than the parkland camera trap sites of Moll et al. (2020) located in mesic northern Ohio, USA.

Management Implications

The choice of what camera trap model to use for wildlife surveys should always consider the user's research or management objectives (Rovero and Zimmermann 2016). For rare species with low capture probabilities, users may prefer the Browning camera trap which, despite its high rate of false positives, also had a higher incidence of positive detections. Conversely, users with limited time or resources to address false positive images may prefer the Grizzly Systems camera trap that provided fewer false positives but at the cost of fewer positive detections. However, the capabilities of AI are progressing rapidly, and the tradeoff between a very low rate of false positives and fewer positive detections may not be an issue in future versions of the Grizzly Systems camera trap. Overall, the Grizzly Systems and Reconyx camera traps averaged 78% correct actions, outperforming the Browing camera trap that averaged 41% correct actions. Notably, however, the Grizzly Systems camera trap was more likely than Reconyx to provide correct actions when air temperatures exceeded 30 °C. Finally, my results indicate that air temperatures, and to a lesser degree wind speeds, may bias camera trapping estimates of wildlife population abundance or occupancy. Furthermore, increased air temperature increased the probability that the Grizzly Systems and Reconyx camera traps would miss detections, but not the Browning camera trap. This could bias wildlife population estimates if multiple models of camera traps are used in the same survey. Further research is warranted to assess the magnitude of bias that may be introduced into population modeling efforts due to the effects of environmental factors at camera trap sites.

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CHAPTER FOUR

STUDY 2: CELLULAR-CONNECTED CAMERA TRAPS

Introduction

Camera trapping has become a widely accepted, non-invasive method for wildlife surveys, and is increasingly prevalent in wildlife research and management (Karanth and Nichols 1998, Cutler and Swann 1999, Tobler et al. 2008, Kays et al. 2009, Burton et al. 2015). However, traditional camera trap data are not “real-time”, meaning that camera trap images must be retrieved from the field, processed, and analyzed. This is a critical gap in situations demanding immediate wildlife management actions, such as wildlife-livestock conflict mitigation or anti-poaching efforts (Dertien et al. 2023, Whytock et al. 2023). In response, many contemporary camera trap manufacturers have integrated cellular data connectivity with camera traps, enabling the transmission of camera trap images in real-time. In areas with cellular coverage, camera trap connectivity allows for remote viewing of low-resolution images sent by the camera trap to a phone application or email (Dertien et al. 2023). For more remote areas without reliable cellular coverage, similar alternatives exist to connect camera traps with long-range radio or satellite networks (Whytock et al. 2023). Real-time notifications of wildlife presence enable practitioners, such as ranchers or wildlife managers, to take management actions when and where they are most effective.

Unfortunately, currently available cellular-connected camera traps can send large numbers of images, including many false positive (i.e., blank) images, in a short period of time, which wastes time and resources, and may overwhelm practitioners (Whytock et al. 2023). A partial solution has involved developing camera traps that use artificial intelligence (AI) to capture fewer false positive images. An additional solution could be to deploy AI-enabled camera traps that use an automated, post-capture image classifier that would enable cellular-connected camera traps to only send images that contain wildlife, or only send images of a practitioner's focal species of wildlife, which is a transformative step towards monitoring and subsequent management decisions based on information received in near real-time (Dertien et al. 2023, Whytock et al. 2023). For example, Dertien et al. (2023) described the use of Trailguard AI camera traps for mitigating human-tiger (*Panthera tigris*) conflicts in India. The camera traps used edge-AI image classification and cellular connectivity to send real-time notifications of tiger or human detections to email or a smartphone application (e.g., Telegram or Whatsapp; Dertien et al. 2023). Whytock et al. (2023) combined edge AI with camera traps to classify images and send real-time alerts of wildlife detections over the Iridium satellite network in a region of Africa that lacked a cellular network. Image classification was limited to 3 categories of elephant, human, or "other" to limit computation time and associated energy draw on batteries. To increase efficiency and reduce the high cost of data transfer over a satellite network, notifications consisted of only the image timestamp, species classification, and camera trap battery status, and the actual image was stored on the camera trap's SD card. Whytock et al. (2023) discussed the potential for the volume of notifications to become overwhelming and suggested reducing the amount of data sent in real-time by adapting methodology to send notifications about events (i.e., the same individual or species captured in multiple images) rather than sending notifications of singular images.

A connected camera trap used for real-time wildlife monitoring must be able to efficiently send images containing animals (i.e., positive detections), without sending large numbers of blank images (i.e., false positives). Additionally, a notification system used with the connected camera trap should reduce the total volume of data sent to the end-user, thus preventing the end-user from being overwhelmed with the number of notifications received, but without sacrificing information on animals detected. The Grizzly Systems camera trap (Grizzly Systems, Bozeman, MT) is a novel, never-before-tested camera trap that is engineered to leverage edge-AI to reduce false positive images by evaluating thermal anomalies in its detection zone prior to image capture. The cellular-connected version of the Grizzly Systems camera trap uses an automated, post-image capture processing workflow to classify images and reduce the number of notifications received by the end-user. The objective of this study was to evaluate the performance of the Grizzly Systems connected camera trap and notification system by comparing it to notifications sent by a Reconyx Hyperfire 2 (Reconyx, Inc., Holmen, WI), which is a traditional cellular-connected camera trap without AI or automated image classification capabilities. Notification performance was assessed by quantifying the total number of images received, notifications containing positive detections, false positive images, and the ratio of actionable images (Table 6).

Table 6. Email notification responses used to assess the performance of cellular-connected camera traps tested during spring 2023 in south-central Montana, USA.

Notification Responses	Definition
Total Images	Total number of notifications received.
Positive Detections	Notification contained image with animal present.
False Positives	Notification contained image with no animal present (i.e., blank image.
Actionable Images	Aggregate variable quantifying notification efficiency. Ratio of notifications containing positive detections to the total number of notifications.

Study Area

This study was conducted at lower elevation sites (~1500 m) located about 8 km southwest of Emigrant, MT, in the Greater Yellowstone Ecosystem in south-central Montana, north of Yellowstone National Park (YNP) within the Northern Yellowstone Range (NYR; Mosley et al. 2018). The NYR outside YNP is a working landscape comprised of multiple-use federal and state lands, ranches, and other private lands that provide critical winter and summer habitat for wildlife (Mosley et al. 2018). Wild ungulate species in the study area include Rocky Mountain elk (*Cervus elaphus nelsoni*), Rocky Mountain mule deer (*Odocoileus hemionus hemionus*), white-tailed deer (*O. virginianus canadensis*), pronghorn (*Antilocapra americana*), and Rocky Mountain bighorn sheep (*Ovis canadensis canadensis*). Domestic ungulates cohabiting the NYR include cattle (*Bos taurus*), sheep (*Ovis airies*), and horses (*Equus caballus*). Several predator species also cohabit the low elevation areas in the NYR, including red fox (*Vulpes vulpes*), coyotes (*Canis latrans*), bobcats (*Lynx rufus*), and mountain lions (*Puma concolor*). Other large predators inhabit the NYR and occasionally occur in lower elevation areas [grizzly bears (*Ursus arctos horribilis*), black bears (*Ursus americanus*), and wolves (*C. lupus*)]. Vegetation generally consists of irrigated pastures and hayfields at low elevations, with foothill grasslands and sagebrush steppe at mid-elevations. Dominant native plant species include bluebunch wheatgrass (*Pseudoroegneria spicata*), Idaho fescue (*Festuca idahoensis*), Columbia needlegrass (*Stipa nelsoni*), mountain big sagebrush (*Artemisia tridentata* ssp. *vaseyana*), and Rocky Mountain juniper (*Juniperus scopulorum*; Mueggler and Stewart 1980).

Methods

I assessed the performance of the Grizzly Systems and Reconyx camera trap models in a field setting using methods similar to Jacobs and Ausband (2018). A camera trap group consisted of one of each camera trap model (Grizzly Systems and Reconyx) mounted side by side in random order, and positioned at the same height and angle to minimize bias caused by differences in the camera trap field of view (Wellington et al. 2014; Figure 7). I deployed five such camera trap groups for a field test from 22 April to 14 June 2023. Camera trap group placement prioritized areas likely to encounter wildlife, such as near game trails and gates in fences (Iannarilli et al. 2021). Sites were located across 3 ranches, and were placed exclusively on private property to mitigate the risk of theft. Camera trap groups were spaced ≥ 100 m apart.

Camera trap groups were mounted on trees, wooden fence posts, or steel t-posts approximately 75 cm from ground level to optimize detection of large animals. Low-hanging branches and dense vegetation within 1 m in front of the camera trap group were cleared upon initial deployment and as needed throughout the study. Both camera trap models were set to high sensitivity, 1 image per trigger, and a 3-second (Grizzly) or 5-second delay (Reconyx). The delay on the Grizzly Systems' camera trap was not adjustable, and the shortest delay possible for the

Reconyx camera trap was 5 seconds. A woven wire exclosure was placed around the camera trap group to prevent damage from wildlife or livestock. Camera trap sites were visited weekly to exchange SD cards and monitor battery levels. Both camera trap models were connected to cellular data using the T-Mobile network (T-Mobile US, Inc., Bellevue, WA), and images collected by both camera trap models were sent to the same email. Images of humans and vehicles were not included in the analysis.

Figure 8. Example camera trap group tested during spring 2023 in south-central Montana, USA: Grizzly Systems (L) and Reconyx Hyperfire 2 Cellular (R).

The Reconyx camera traps sent all captured images directly to the project email, providing a straightforward but unfiltered stream of data. The Grizzly Systems camera traps used an alternative workflow to pre-process data based on identified events prior to sending email notifications. The Grizzly Systems camera trap captured images until ≥ 30 s had passed since the last image had been captured. Next, the Grizzly Systems camera trap connected to the cellular network and uploaded the captured images – referred to as an event – to a server. Once the server received an event, it classified the images using MegaDetector v5a (Beery et al. 2019). Any images classified as blank (MegaDetector confidence < 0.20) were discarded, and only images that contained an animal, human, or vehicle were sent as notifications. If an event contained more than 3 images, the event was further processed to identify the first, the most thermally anomalous ("hottest"), and last image within the batch received by the server. The three identified images (first, hottest, last) were sent as individual email notifications. It is important to note that the Grizzly Systems camera traps could not trigger and capture new images while they were connected to the network. I was unable to quantify this "blind period", as it varied depending on the number of images being sent and the cellular network conditions at the time of connection.

All image notifications were manually reviewed and categorized as positive detections (containing an animal) or false positives (blank images without an animal). A third response variable, "actionable images", was defined as the daily ratio of positive detections to total notifications. Actionable images created a metric by which to assess the practical utility of a camera trap model for a potential end-user by quantifying the proportion of images providing opportunities to employ management actions (positive detections) vs. images that create informational noise and waste time and energy (false positives), although it does not consider any missed detections. I restricted my data analysis to time periods when both camera traps at a site were functioning properly, resulting in the exclusion of 3 camera trap sites due to persistent equipment malfunctions and compromised data quality. For the 2 remaining sites, I grouped email notifications by day, and differences between camera trap models were assessed using Wilcoxon Signed Rank Tests ($P \leq 0.05$) for total images, positive detections, false positives, and actionable images.

Results

I received 7,578 email notifications from the 2 camera trap sites over 41 days of the study period. Wilcoxon Signed Rank Tests revealed statistical differences between the Grizzly Systems and Reconyx camera trap models for total images ($P < 0.001$), positive detections ($P < 0.001$), false positives ($P < 0.001$), and actionable images ($P = 0.004$, Figures 9 and 10). The Reconyx camera traps sent a total of 6,970 image notifications, and the Grizzly Systems camera traps sent a total of 608 image notifications. Of the total images received, Grizzly Systems sent 602 positive detections and 6 false positives. All 6 false positive images received were the result of a misclassification by MegaDetector, rather than an error by the Grizzly Systems server. Reconyx sent 5,061 positive detections and 1,909 false positives (Figure 8). When considered from the perspective of an end-user, 99.1% and 72.6% of the images received from the Grizzly Systems and Reconyx camera traps, respectively, were actionable images (Figure 9).

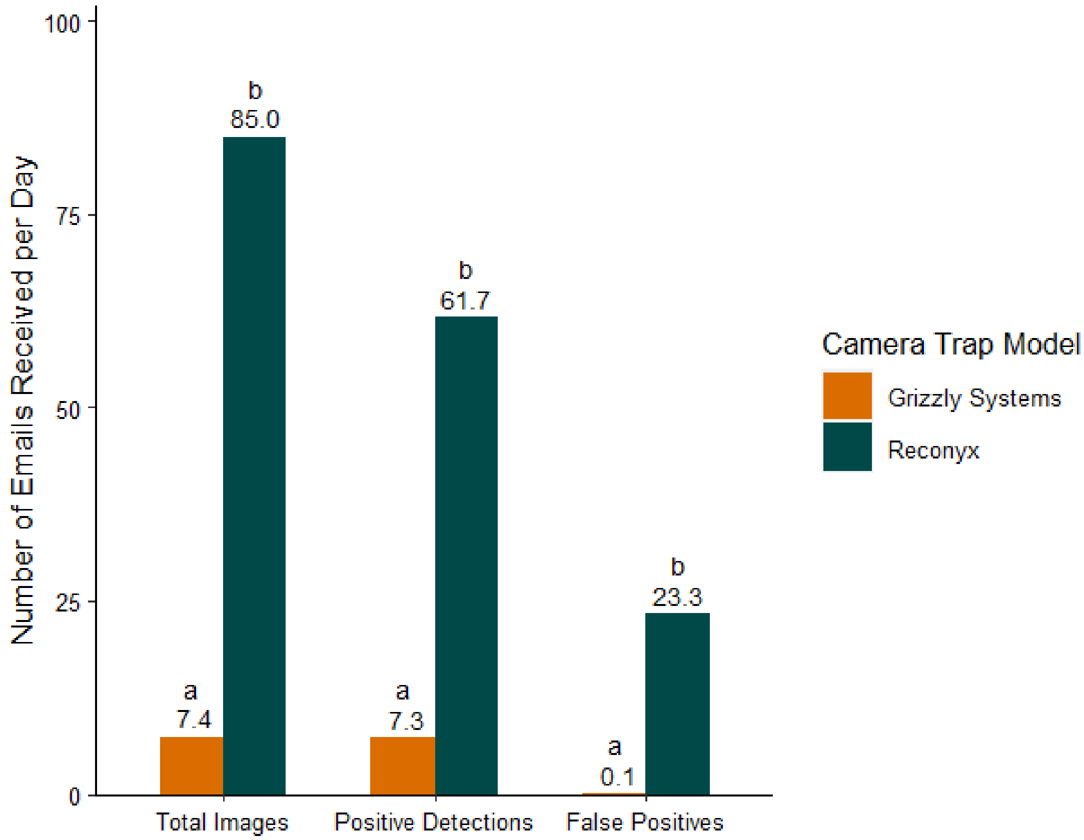

Figure 9. Average number of email notifications received per camera trap per day for the response variables of total images, positive detections, and false positives from 2 cellular-connected camera trap models tested during spring 2023 in south-central Montana, USA. Values within response variables with the same lowercase letter are not different (*P* > 0.05).

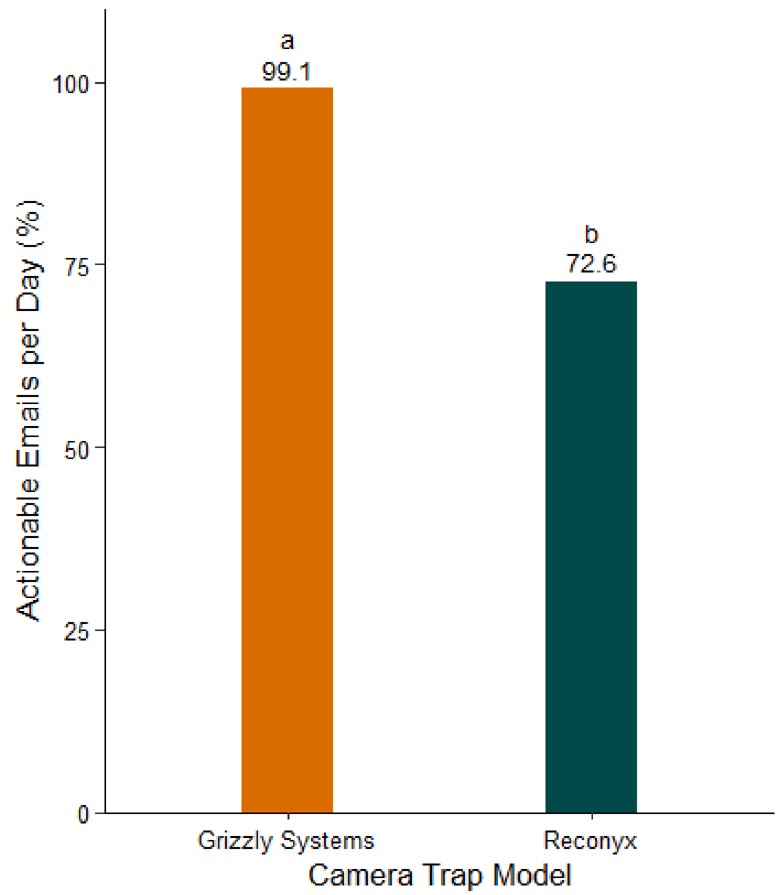

Figure 10. Percentage of actionable image emails received per camera trap per day from 2 cellular-connected camera trap models during spring 2023 in south-central Montana, USA. Values with the same lowercase letter are not different (*P* > 0.05).

The Grizzly Systems camera trap's image processing workflow was designed to limit the volume of email notifications by sending only 3 notifications whenever more than 3 images were captured in a single event. However, on 54 occasions the Grizzly Systems camera trap sent more than 3 notifications after a single event. These 54 occasions should have resulted in 162 email notifications rather than the 329 notifications that were received. It is unknown why this occurred.

Discussion

The Grizzly Systems cellular-connected camera trap sent substantially fewer email notifications than the Reconyx cellular-connected camera trap. Additionally, the Grizzly Systems camera trap nearly eliminated sending false positive images. Other than the false positive images misclassified by MegaDetector, the Grizzly Systems camera trap sent no false positive images, and 99% of the notifications delivered contained images of animals (positive detections). In contrast, only 73% of the images sent by Reconyx contained animals. The Grizzly Systems camera trap also reduced the number of notifications received by limiting the number of images sent when a capture event contained more than 3 images, but this aspect of the Grizzly Systems workflow did not always work as intended.

Each cellular-connected Reconyx camera trap averaged 61.7 notifications of positive detections per day vs. 7.3 positive detection notifications per day from each of the cellular-connected Grizzly Systems camera traps. Some of this difference is attributable to the Grizzly Systems workflow that intentionally reduced notifications of positive detections whenever more than 3 images were captured in a single event. It is also possible that the blind period, when the Grizzly Systems camera trap is unable to capture new images while sending data to the server, could have resulted in missed detections if animals were present during this time. Missed detections could also have occurred if the Grizzly Systems camera trap simply failed to trigger. However, my results from Study 1 (see Chapter 3 of this thesis) indicated that unconnected Grizzly Systems camera traps had a missed detection rate of 21%, a rate too low to account for the entire difference in email notifications of positive detections transmitted between the Grizzly Systems and Reconyx cellular-connected camera traps. Further investigation is needed to address this issue, because the benefits of reducing the total volume of notifications are significantly reduced if the camera trap fails to detect an animal.

My research differs from similar studies exploring real-time notifications using camera traps and AI (Dertien et al. 2023, Tulasi et al. 2023, Whytock et al. 2023), as the Grizzly Systems camera trap used edge-AI at the trigger level to reduce false positives and increase efficiency, rather than relying solely on post-image capture processing using machine learning. Refinement of the AI-enabled trigger could potentially reduce the computational needs after an image is captured, further enhancing the Grizzly Systems camera trap efficiency. It is also noteworthy that Dertien et al. (2023), Tulasi et al. (2023), and Whytock et al. (2023) all used species-specific image classifiers that were trained specifically for their projects. The Grizzly Systems workflow did not use a species-specific image classifier, but rather capitalized on a highly accurate, open-source object detection model that categorized images to the level of animal, person, or vehicle (MegaDetector). Currently available, open-source, species-specific image classifiers (e.g., CameraTrapDetectoR) report accuracies that are lower than desired for many target species in my study area (e.g., elk and domestic cattle; Tabak et al. 2022).

Management Implications

A camera trap with the ability to send real-time, pre-processed images would be a valuable innovation in wildlife management, where decision-making often occurs on short timelines and has profound implications on both wildlife conservation and human livelihoods. My study documents exploration into one strategy for real-time wildlife monitoring that attempts to modulate the amount of information received by an end-user. Reducing the volume of information received will be vital as real-time wildlife monitoring expands across large landscapes and is integrated into larger, more complex camera trap networks. While this study identified unresolved questions about the Grizzly Systems cellular-connected camera trap, it provides novel proof of concept relevant to real-time wildlife monitoring and mitigation of human-wildlife conflicts. My results also help highlight strategies for improving cellular-connected camera trap technology to continue to meet the demands of wildlife management and human-wildlife conflict mitigation.

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CHAPTER FIVE

CONCLUSION

A camera trap that captures few false positive images and provides real-time wildlife monitoring would enhance the efficiency of wildlife surveys using camera traps as well as be a significant innovation for active wildlife monitoring. In Study 1, the Grizzly Systems camera trap greatly reduced the capture rate of false positive images compared to Browning or Reconyx camera traps. Browning and Reconyx camera traps were 99 and 6 times more likely, respectively, to capture a false positive image. However, the Grizzly Systems camera trap had a lower probability of capturing animals, being 5 and 2.5 times less likely to capture a positive detection than the Browning or Reconyx camera traps, respectively, which identifies a need to further refine the AI-enabled trigger. Overall, the Grizzly Systems camera trap was 82% more likely than Browning to perform a correct action, and with no significant difference in the performance of correct actions between Grizzly Systems and Reconyx camera traps.

Across all 3 camera trap models, there was a noticeable decrease in positive detections as air temperature and wind speed increased. This trend merits further investigation due to its implications for accurately estimating detection probabilities, which are essential in certain population modeling approaches, such as those used for determining abundance or occupancy. Warmer air temperatures increased the capture probability of false positives by Browning and Reconyx camera traps, but Grizzly Systems camera traps were less likely to capture false positives as air temperature increased. The effect of air temperature on missed detections and correct actions varied by camera trap model. Browning camera traps were less likely to miss detections as air temperature increased, but much less likely to perform correct actions, while the reverse was true for Grizzly Systems camera traps. Air temperature had a slight negative effect on whether the Reconyx camera traps missed detections, but relatively little effect on whether Reconyx camera traps performed correct actions. Increased wind speeds decreased the likelihood of positive detections, but wind speed did not affect false positives, missed detections, or correct actions. Cloud cover and vegetation type had no substantive effects on camera trap performance.

In Study 2, the cellular-connected Grizzly Systems camera trap successfully provided real-time notifications of wildlife presence with automated data processing and notification reduction. Excluding the few blank images that were misclassified by MegaDetector as containing an animal, the Grizzly Systems camera trap sent no notifications containing false positive images. However, the workflow of the Grizzly Systems cellular-connected camera trap did not adequately limit the number of email notifications. Concurrently, the Grizzly Systems camera trap sent substantially fewer notifications of positive detections compared to the cellular-connected Reconyx camera trap. The causes of these issues were unidentified and warrant further investigation.

Overall, this study underscores the promise and the real-world challenges of developing and integrating advanced technology into wildlife research and management. A system with edge-AI processing and customizable image processing workflow presents a substantial advancement in camera trap technology, but the limitations observed in my study suggest that further refinement is necessary it can be widely adopted by wildlife researchers and managers.

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