DRONE SYMPOSIUM: DRONE APPLICATIONS IN WILDLIFE AND SPATIAL ECOLOGY

Abstracts and Presentations – Part 2

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Sponsored by:
TWS Drone Working Group

and

Spatial Ecology & Telemetry Working Group

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Abstract: Wildlife biologists are relying on an ever-increasing suite of tools to answer questions and solve problems related to wildlife ecology, management, and conservation. The use of unoccupied aerial vehicles, UAVs or drones, has exploded in popularity in ecological studies in general, and in wildlife biology in particular. Drones have many advantages over traditional research techniques. They eliminate safety risks associated with fixed-wing and helicopter surveys, reduce cost and disturbance, increase accuracy, and allow the collection of high-resolution data over large or otherwise inaccessible areas. Some of the major areas of application of drones that have emerged in wildlife ecology include, but are not limited to: (1) population surveys, including breeding colonies and non-breeding aggregations and the use of different types of sensors (e.g.); (2) nest monitoring; (3) radio-tracking surveys; (4) acoustic surveys; (5) wildlife habitat research and monitoring; (6) the use of different drone sensors (e.g., visible, thermal IR, multi- and hyperspectral); and (7) wildlife dispersal, either for nuisance or invasive species or to deter from hazards. This symposium provides highlights of the use of drones in wildlife and spatial ecology and a forum for discussion among both experts and potential users of drones that may result in future research collaborations between wildlife biologists in academic, government, and private sectors.

LIST OF PRESENTATIONS

PART 1

Introduction to the Drone Working Group and Spatial Ecology & Telemetry Working Group – Spaulding & Jenness
Developing a Drone Program for Wildlife and Habitat in an Academic Setting – Perotto-Baldivieso et al.
Overview of the University of Florida Uncrewed Aircraft Systems Research Program (UFUASRP): Two Decades of Drones for Natural Resource Applications – Carthy et al.
Drones and Computer Vision as a Potential Method for Bird Carcass and Bird Nest Detection at Solar Energy Facilities – Gerringer et al.
Using Drones & AI for Wildlife Surveys: Detecting Avian Carcasses & Desert Tortoises – M. Bandy
UAS as Wildlife Hazing Tools: Considerations for Reducing Negative Human-Wildlife Interactions – Pfeiffer & Blackwell
Using Drones to Detect and Quantify Wild Pig Damage and Yield Loss in Corn Fields Throughout Multiple Growth Stages – Friesenhahn* et al.

PART 2

***Spraying Drones: Efficacy of Applying an Avian Repellent to Elicit Blackbird Flock Dispersion in Commercial Sunflower Fields* – Duttenhefner* et al.**
***Benefits and Limitations of Using an Uncrewed Aerial Vehicle to Survey Large Mammals in Forest Fragments* – Magee* et al.**
***Evaluation of UAS Surveys for Ungulates in South Texas Rangelands* – Foley et al.**
***White-tailed Deer Surveys with Thermal Drones and Distance Sampling* – Massey* et al.**
***Controllable Factors Affecting Accuracy of Human Identification of Birds in Images Obtained during UAS Surveys* – Jones et al.**
***AI for Detection and Classification of Wildlife from sUAS Imagery* – Boopalan et al.**
***A Systematic Map of Utilizing Small Unoccupied/Uncrewed Aircraft Systems (UAS) to Monitor Wildlife* – Elmore et al.**
***Measuring Bat Occupancy and Abundance Using Drone-based Line Transect Surveys* – Bishop-Boros et al.**
PART 3
Guidelines to Sampling Aerial Canopy Arthropods with UAVs – Madden et al.
Small Uncrewed Aircraft Systems and Artificial Intelligence: A New Approach for Monitoring Waterfowl Response to Wetland Restoration – Loken* & Ringelman
Drones, Structure from Motion, and the Digital Twin: Lessons Learned Trying to Model Spring Habitats – Jenness et al.
Using 3D Photogrammetry to Measure Vegetation Recovery and Gopher Tortoise (Gopherus polyphemus) Response to Re-Introduction on Reclaimed Mine Lands – Hancock* et al.
Hornets, Bats & Bears: Real-time Drone Radio-telemetry for Wildlife and Invasive Species Managers – D. Saunders
Re-Inventing VHF Tracking: How to Avoid the Pitfalls of Aerial Wildlife Monitoring – C. Muller*
Use of Drones to Advance and Scale Invasive Species Eradications on Islands – Sullivan et al.

*Student presentation.

(*Note*: presenters in **bold**)

Spraying Drones: Efficacy of Applying an Avian Repellent to Elicit Blackbird Flock Dispersion in Commercial Sunflower Fields

Jessica Duttenhefner[1], David Kramar[2], Timothy Greives[1], and Page Klug[3]
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Multiple management strategies exist to combat bird damage to agriculture. We explored the effect of combining two existing tools, drones and an avian repellent, to assess the effectiveness of an integrated method to deter large flocks. We evaluated the ability of a spraying drone (DJI AGRAS MG-1P) deploying Avian Control® (i.e., active ingredient: methyl anthranilate [MA]) or a water control to elicit flock reductions or field abandonment by blackbirds foraging in sunflower. In 2021, we conducted 32 spray trials (MA=15 and water=17) from September to October. In the MA trials, 8 resulted in full abandonment, 4 partial abandonment, and 3 no abandonment. In the water trials, 7 resulted in full abandonment, 7 partial abandonment, and 3 no abandonment. We used a non-parametric, random forest modeling approach to determine the relative importance of treatment, landscape, environmental, and flock variables in predicting field abandonment. We found field abandonment was most influenced by wind speed, time of day, and field size (treatment = 10th most important variable) based on the mean decrease in accuracy and node purity when that variable is removed. When controlling for other variables, probability of abandonment was similar for MA and water. With full abandonment, 20% more flocks returned following MA (87%) than water trials (67%). When flock reduction occurred, average decline was 45±9% for MA and 52±9% for water. While the results are preliminary, they inform sunflower producers of the potential benefit of adding an avian repellent when using drones to haze blackbirds and reduce sunflower damage.


Spraying Drones:
Efficacy of applying an avian repellent to elicit blackbird flock dispersion in commercial sunflower fields.
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Extension, Fargo ND
Timothy J. Greives
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Sciences, Fargo ND
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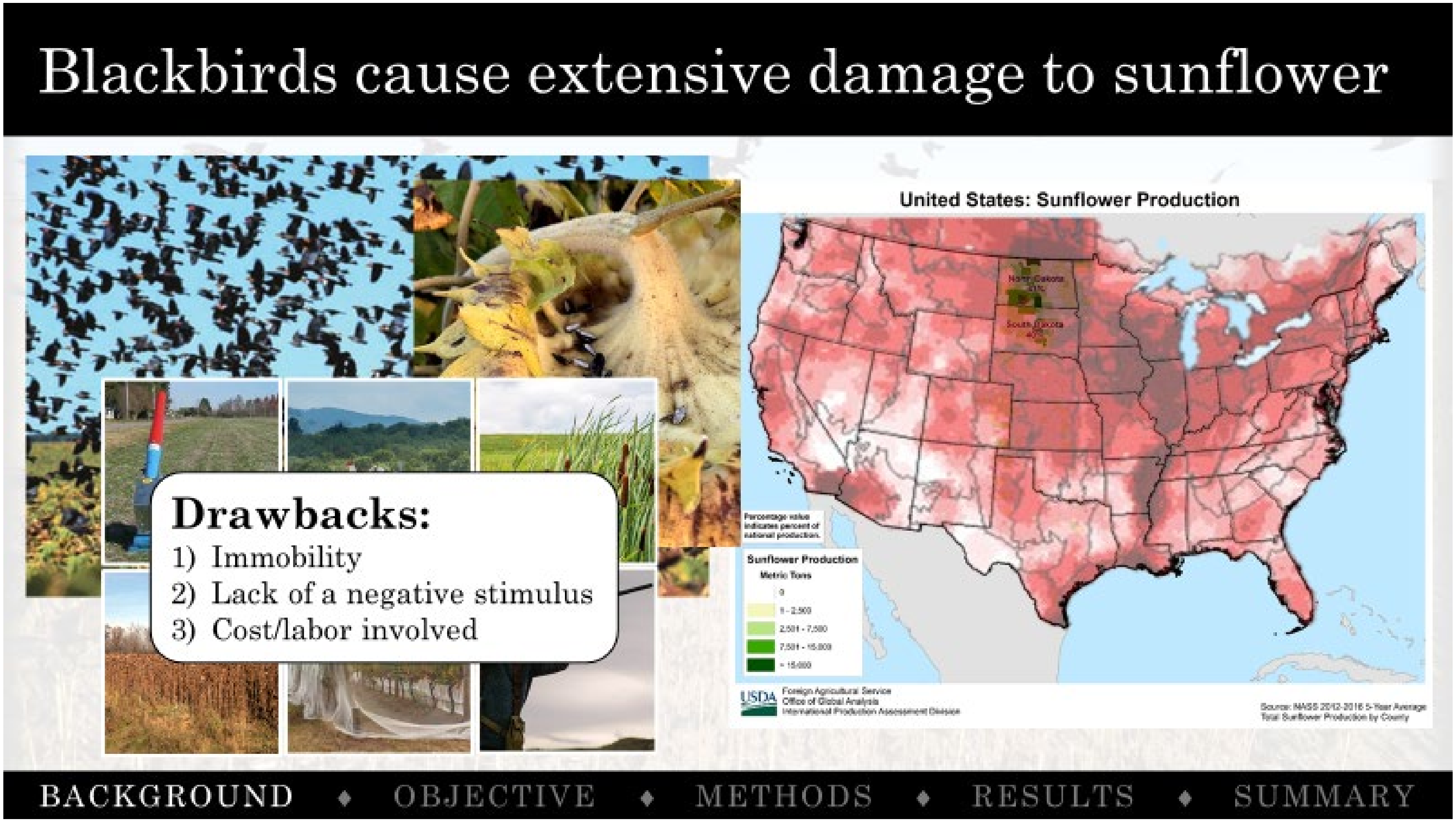
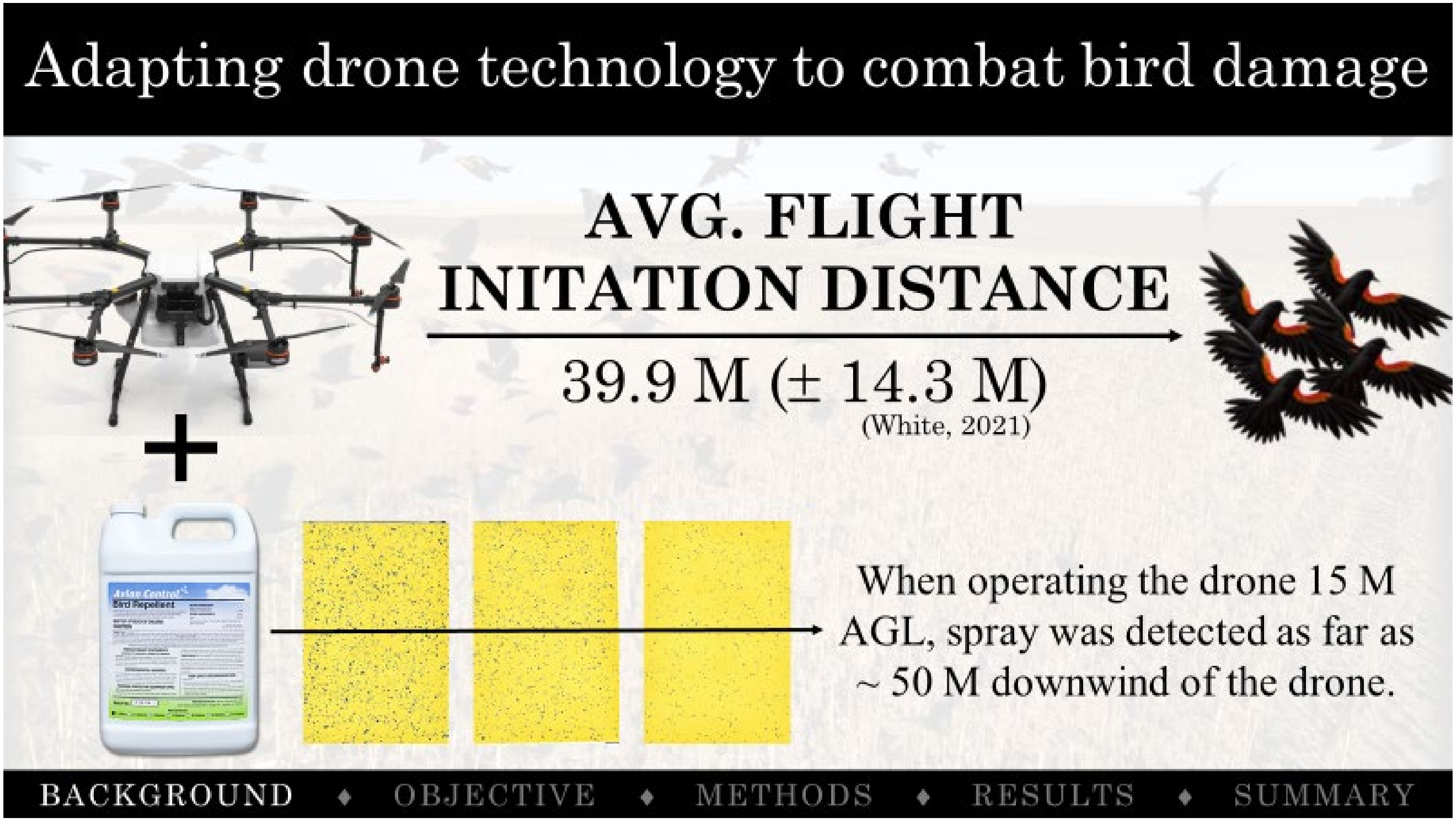
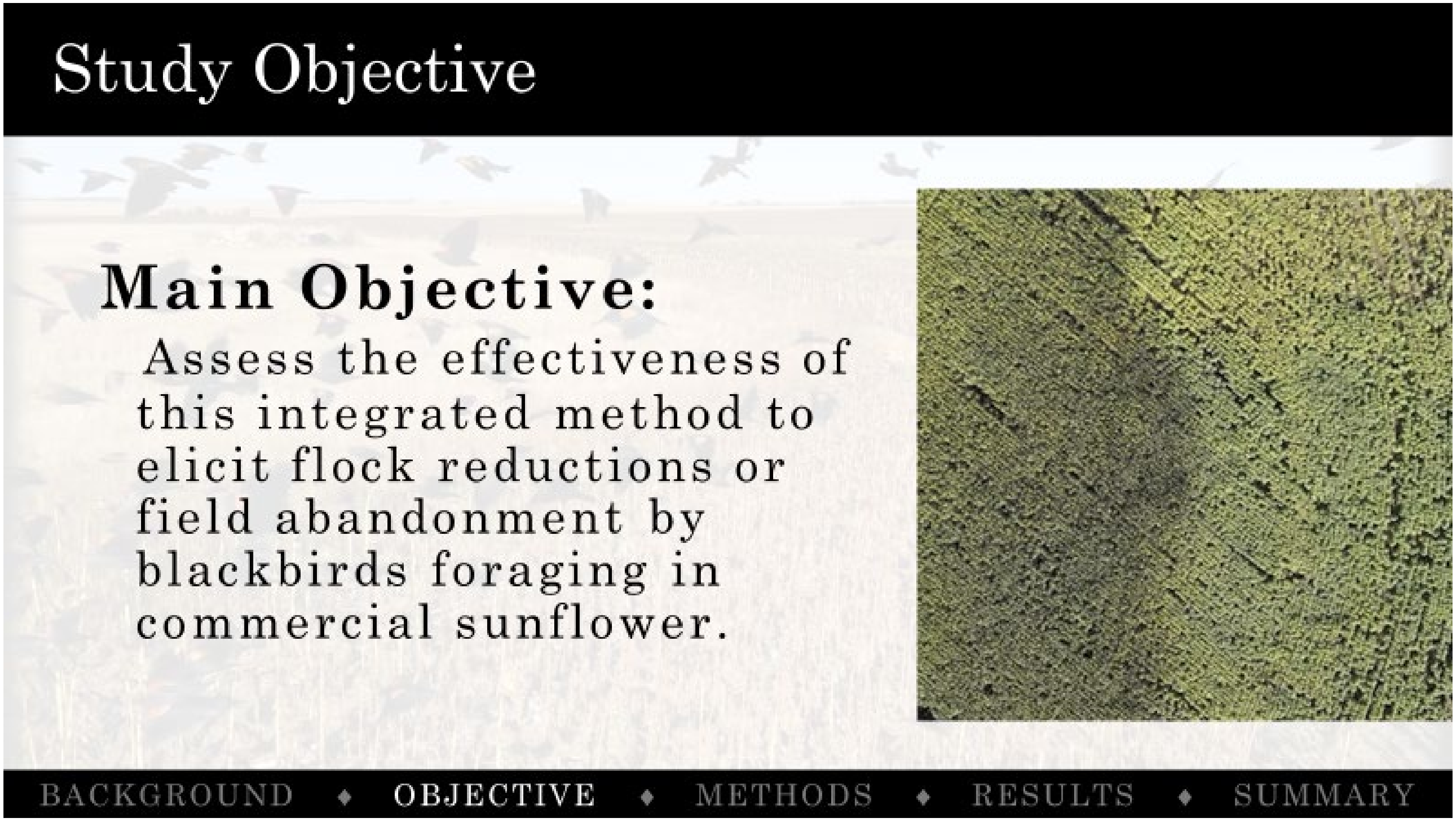
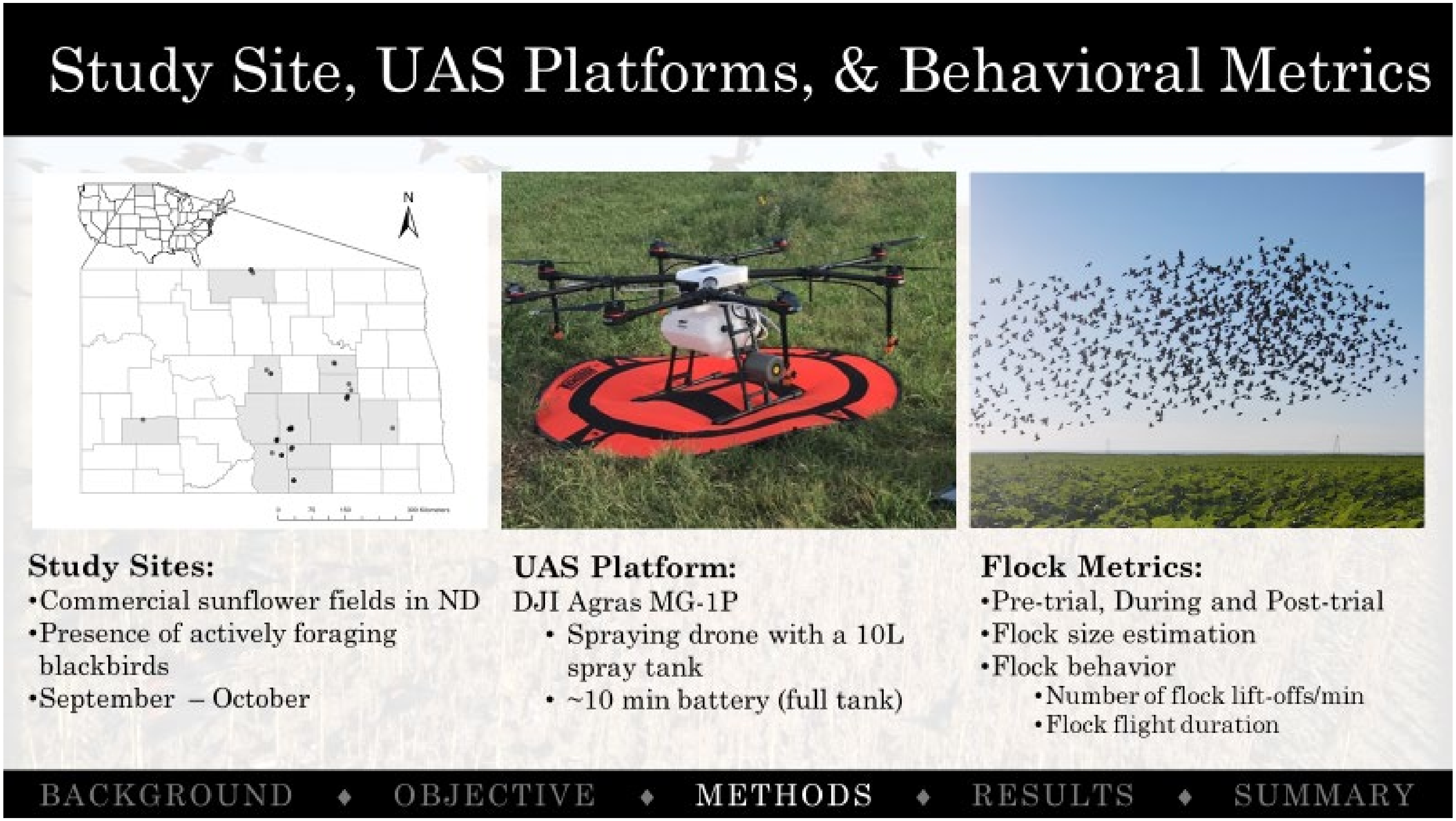
USDA-APHIS-Wildlife Services National Wildlife
Research Center, North Dakota Field Station, Fargo ND

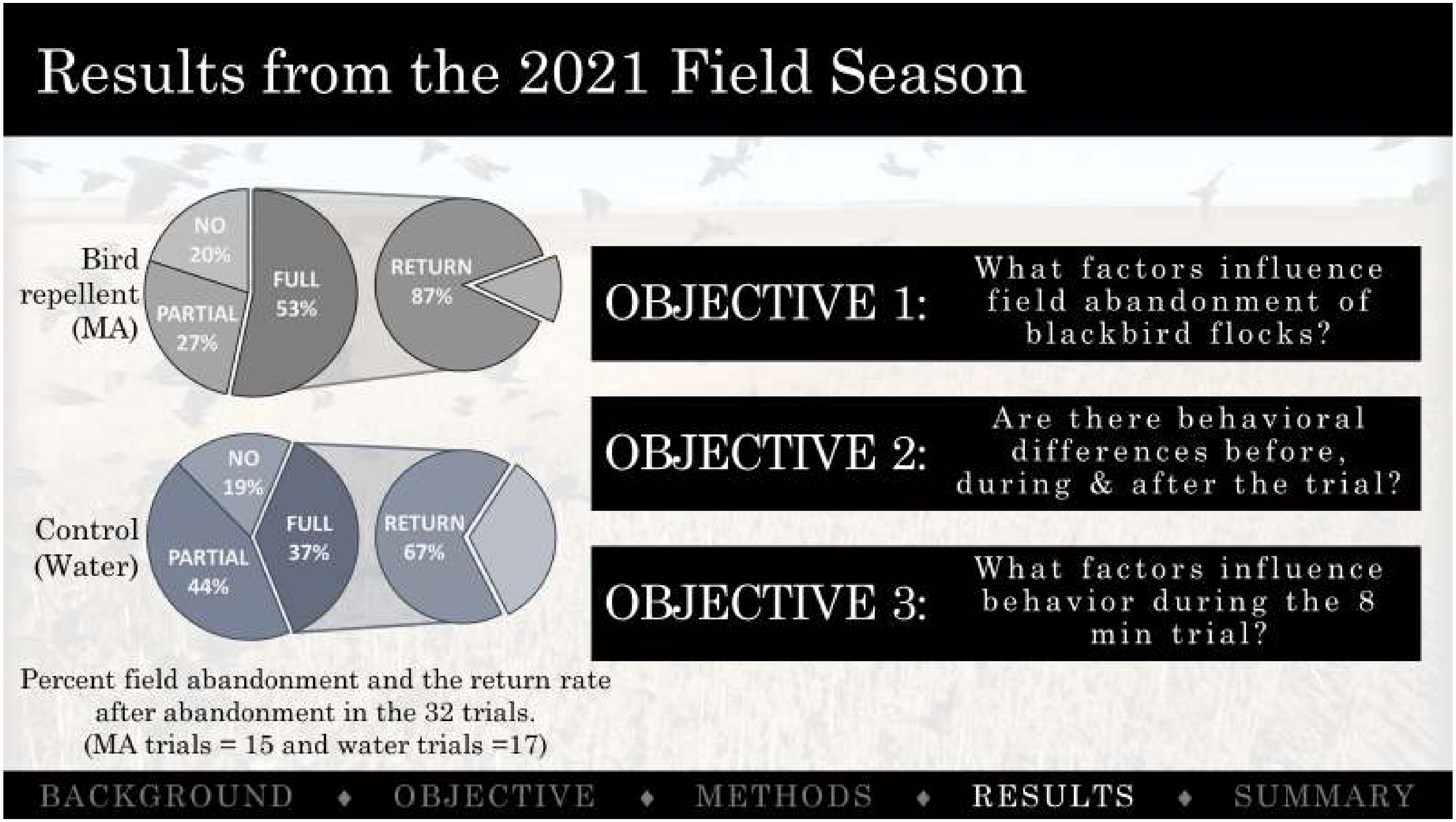

Blackbirds cause extensive damage to sunflower
Drawbacks:
1) Immobility
2) Lack of a negative stimulus
3) Cost/labor involved
United States: Sunflower Production
Percentage value indicates percent of national production.
Sunflower Production
Metric Tons
0
1 - 2,500
2,501 - 7,500
7,501 - 15,000
> 15,000
USDA
Foreign Agricultural Service
Office of Global Analysis
International Production Assessment Division
Source: NASS 2012-2016 5-Year Average
Total Sunflower Production by County
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY

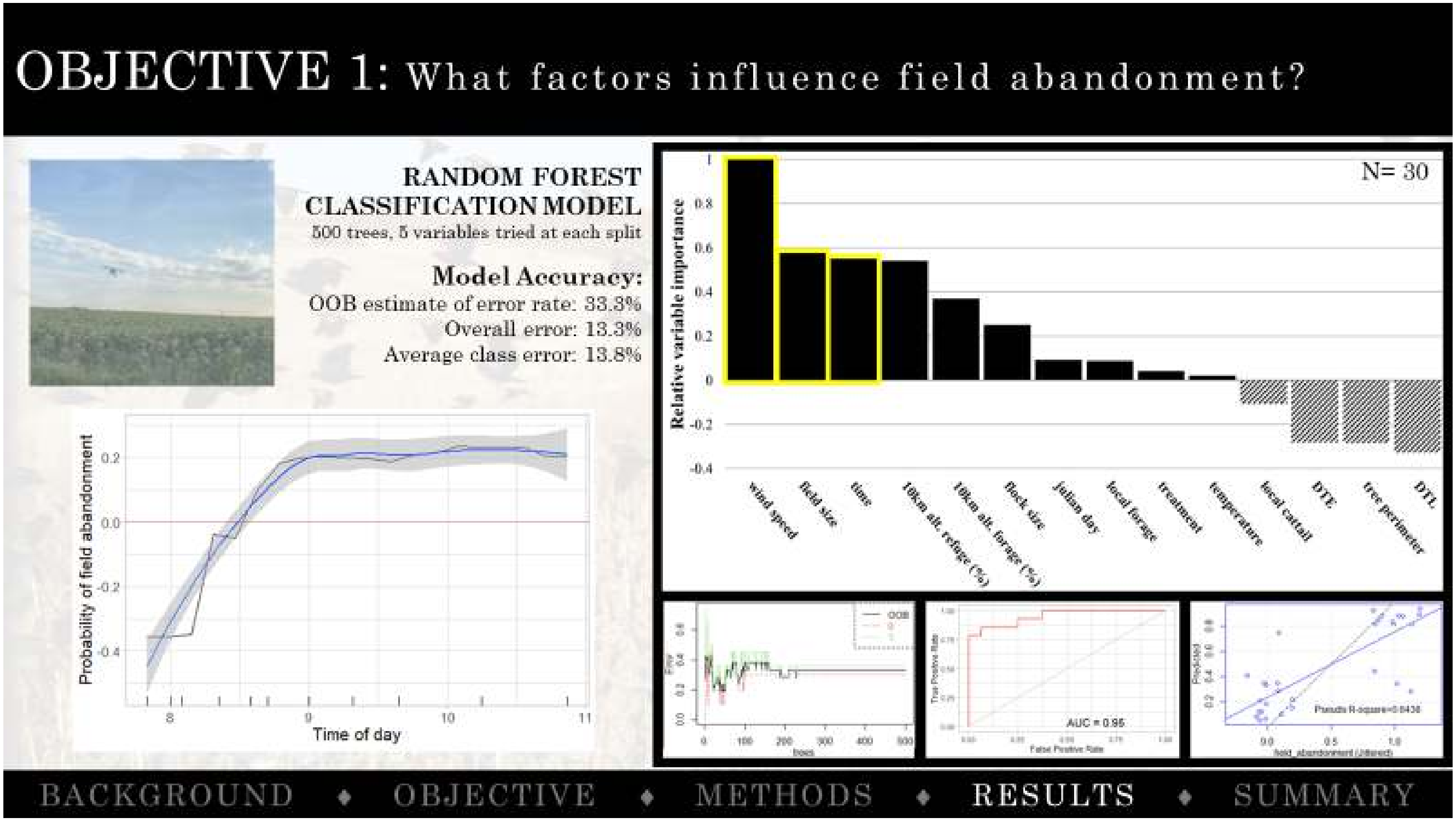

Adapting drone technology to combat bird damage
AVG. FLIGHT INITATION DISTANCE
39.9 M (± 14.3 M)
(White, 2021)
+
When operating the drone 15 M AGL, spray was detected as far as ~ 50 M downwind of the drone.
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY

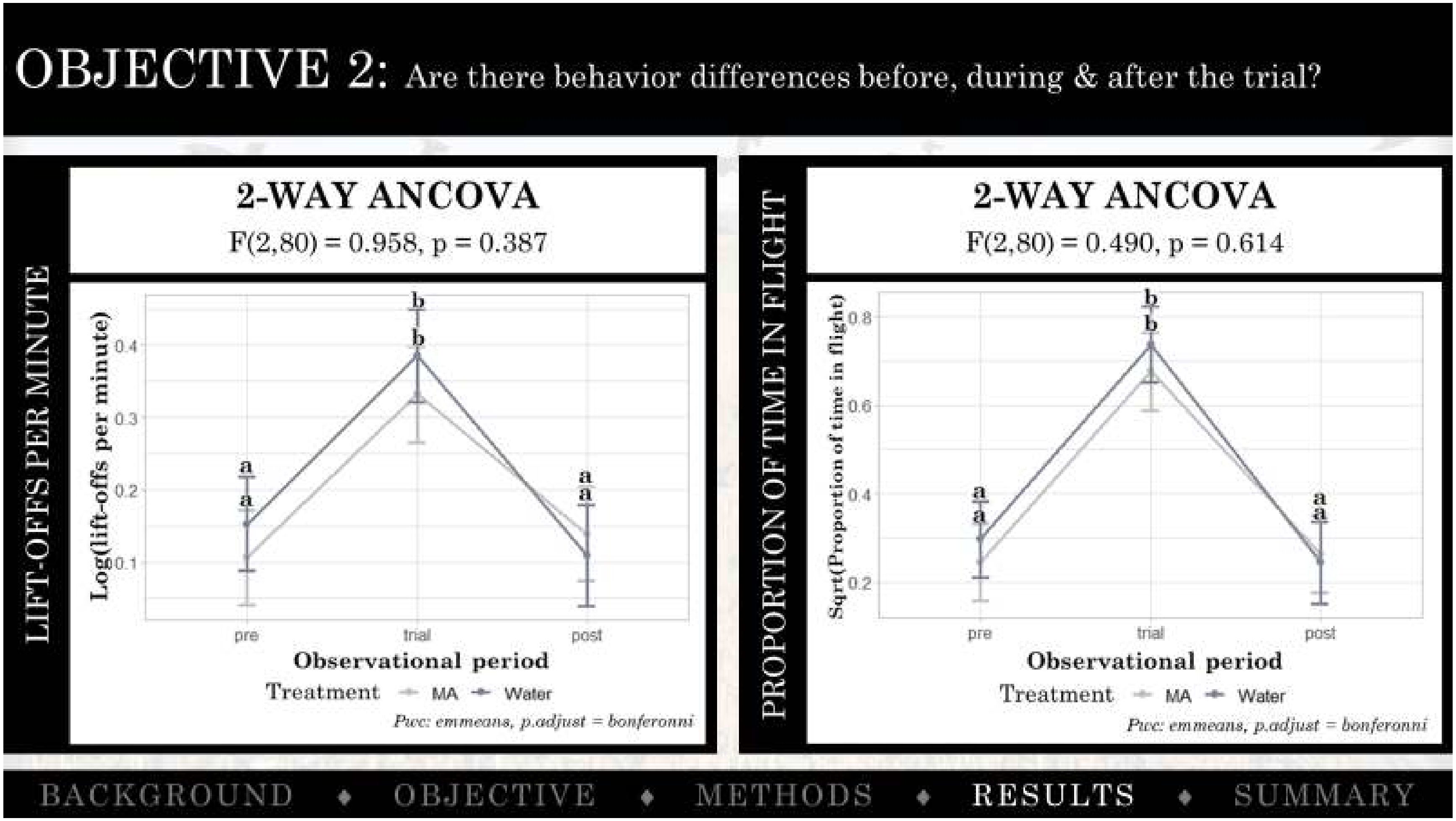

Study Objective
Main Objective:
Assess the effectiveness of this integrated method to elicit flock reductions or field abandonment by blackbirds foraging in commercial sunflower.
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY


Study Site, UAS Platforms, & Behavioral Metrics
N
Study Sites:
•Commercial sunflower fields in ND
•Presence of actively foraging blackbirds
•September – October
UAS Platform:
DJI Agras MG-1P
• Spraying drone with a 10L spray tank
• ~10 min battery (full tank)
Flock Metrics:
•Pre-trial, During and Post-trial
•Flock size estimation
•Flock behavior
•Number of flock lift-offs/min
•Flock flight duration
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY


Study Design
Trials length = 8 minutes
2 treatments:
• Avian repellent application
• Water application
Avian Control®:
• Only avian repellent currently registered for foliar application near harvest.
• Contains methyl anthranilate **(MA)**
• Primary chemical repellent
• Chemically noxious stimuli response
Avian Control™
Bird Repellent
Avian Control™ is formulated with food grade ingredients.
For Commercial and Agricultural Use:
To be used on Agricultural Commodities (Pome Fruit, Stone Fruit, Berry and Small Fruit, Cereal Grains) and Non-Agricultural Sites including Turf, Hydroseeding, Landfills, Non-fish bearing bodies of water, Buildings and Structures.
KEEP OUT OF REACH OF CHILDREN
CAUTION
ACTIVE INGREDIENT
Methyl Anthranilate (MA), methyl 2-aminobenzoate 20.0%
OTHER INGREDIENTS 80.0%
Total 100.0%
This product contains 1.65 pounds of Methyl Anthranilate per gallon of product.
EPA REG. No. 88889-1
EPA EST. No. 33162-MI-01
CERTIFICATIONS:
FAA Part 107 – Small UAG Pilot
FAA Part 137 – Agricultural Pesticide Application
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY


Results from the 2021 Field Season
Bird repellent (MA)
NO 20%
PARTIAL 27%
FULL 53%
RETURN 87%
Control (Water)
NO 19%
PARTIAL 44%
FULL 37%
RETURN 67%
Percent field abandonment and the return rate after abandonment in the 32 trials. (MA trials = 15 and water trials =17)
OBJECTIVE 1: What factors influence field abandonment of blackbird flocks?
OBJECTIVE 2: Are there behavioral differences before, during & after the trial?
OBJECTIVE 3: What factors influence behavior during the 8 min trial?
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY

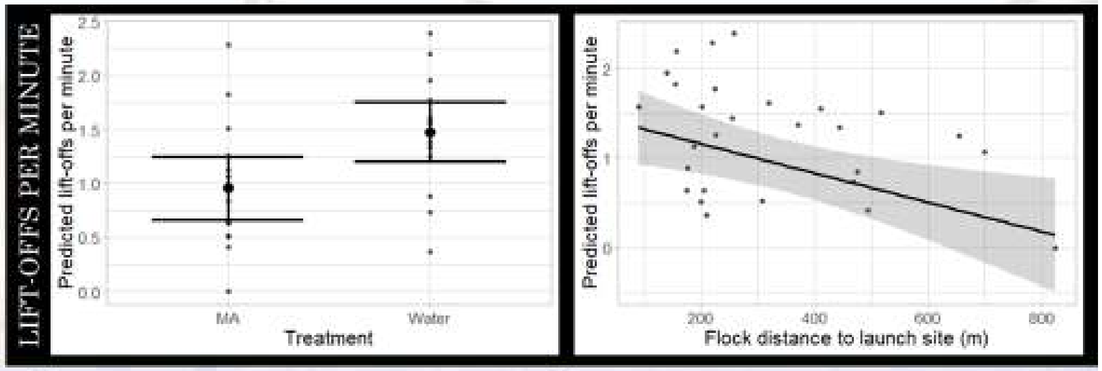

OBJECTIVE 1: What factors influence field abandonment?
RANDOM FOREST CLASSIFICATION MODEL
500 trees, 5 variables tried at each split
Model Accuracy:
OOB estimate of error rate: 33.3%
Overall error: 13.3%
Average class error: 13.8%
Probability of field abandonment
Time of day
N= 30
Relative variable importance
wind speed
field size
time
10km alt. refuge (%)
10km alt. forage (%)
flock size
julian day
local forage
treatment
temperature
local cattail
DTE
tree perimeter
DTL
OOB
AUC = 0.95
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY

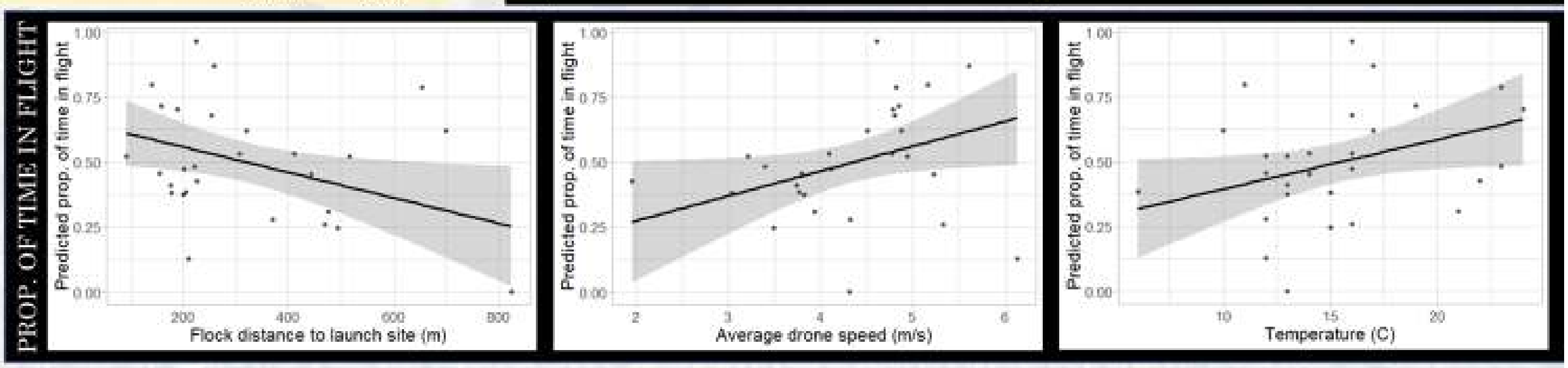

OBJECTIVE 2: Are there behavior differences before, during & after the trial?
LIFT-OFFS PER MINUTE
2-WAY ANCOVA
F(2,80) = 0.958, p = 0.387
Log(lift-offs per minute)
Observational period
pre
trial
post
Treatment MA Water
Pwc: emmeans, p.adjust = bonferonni
PROPORTION OF TIME IN FLIGHT
2-WAY ANCOVA
F(2,80) = 0.490, p = 0.614
Sqrt(Proportion of time in flight)
Observational period
Treatment MA Water
Pwc: emmeans, p.adjust = bonferonni
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY

OBJECTIVE 3: What influences behavioral differences during the trial?

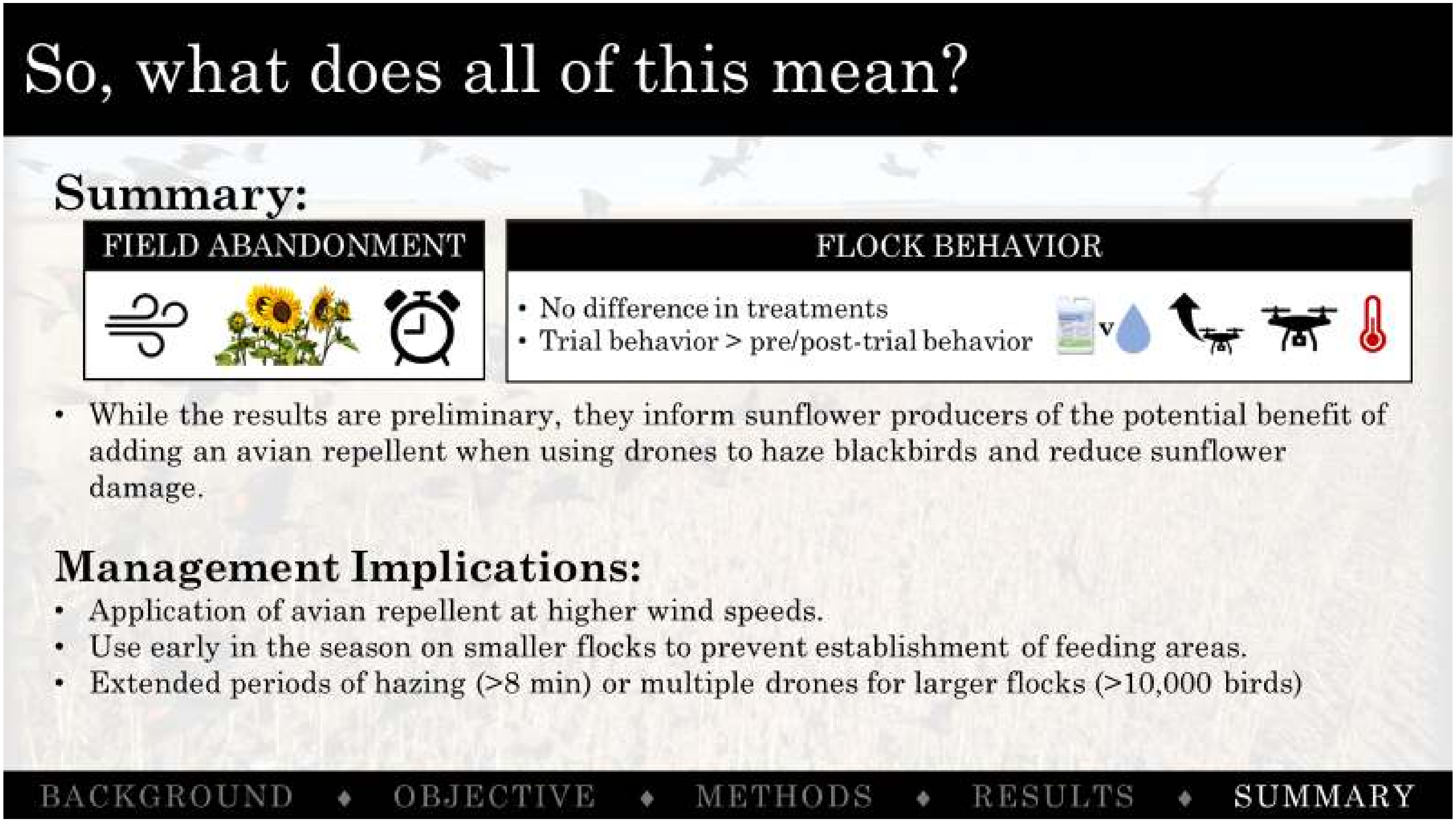
LINEAR MODEL

Parameter	t value	pvalue
A) Trial lift-offs per minute		
(Intercept)	-1.163	0.258
Julian day	1.615	0.121
DTE	1.689	0.105
Field size	-1.837	0.080
Temperature	1.881	0.073
Treatment	2.663	**0.014**
DTL	-2.933	**0.007**
B) Trial proportion of time in flight		
(Intercept)	-0.212	0.834
Temperature	2.124	**0.044**
Drone speed	2.138	**0.043**
DTL	-2.316	**0.029**





BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ **RESULTS** ♦ SUMMARY


So, what does all of this mean?
Summary:
FIELD ABANDONMENT
FLOCK BEHAVIOR
• No difference in treatments
• Trial behavior > pre/post-trial behavior
v
• While the results are preliminary, they inform sunflower producers of the potential benefit of adding an avian repellent when using drones to haze blackbirds and reduce sunflower damage.
Management Implications:
• Application of avian repellent at higher wind speeds.
• Use early in the season on smaller flocks to prevent establishment of feeding areas.
• Extended periods of hazing (>8 min) or multiple drones for larger flocks (>10,000 birds)
BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY

THANK YOU!

Graduate Advisor
- Dr. Page Klug

Committee members
- Dr. Ned Dochtermann
- Dr. Timothy Grieves
- Dr. David Kramar

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- Mallory White
- Morgan Donaldson

Bird Lab
- Heidinger Lab
- Greives Lab

UAS Technicians
- Melissa Baldino, Avalon Cook, Shayly Van Ert

Sunflower Producers

Funding Source
- National Sunflower Association

National Sunflower Association

NDSU NORTH DAKOTA STATE UNIVERSITY

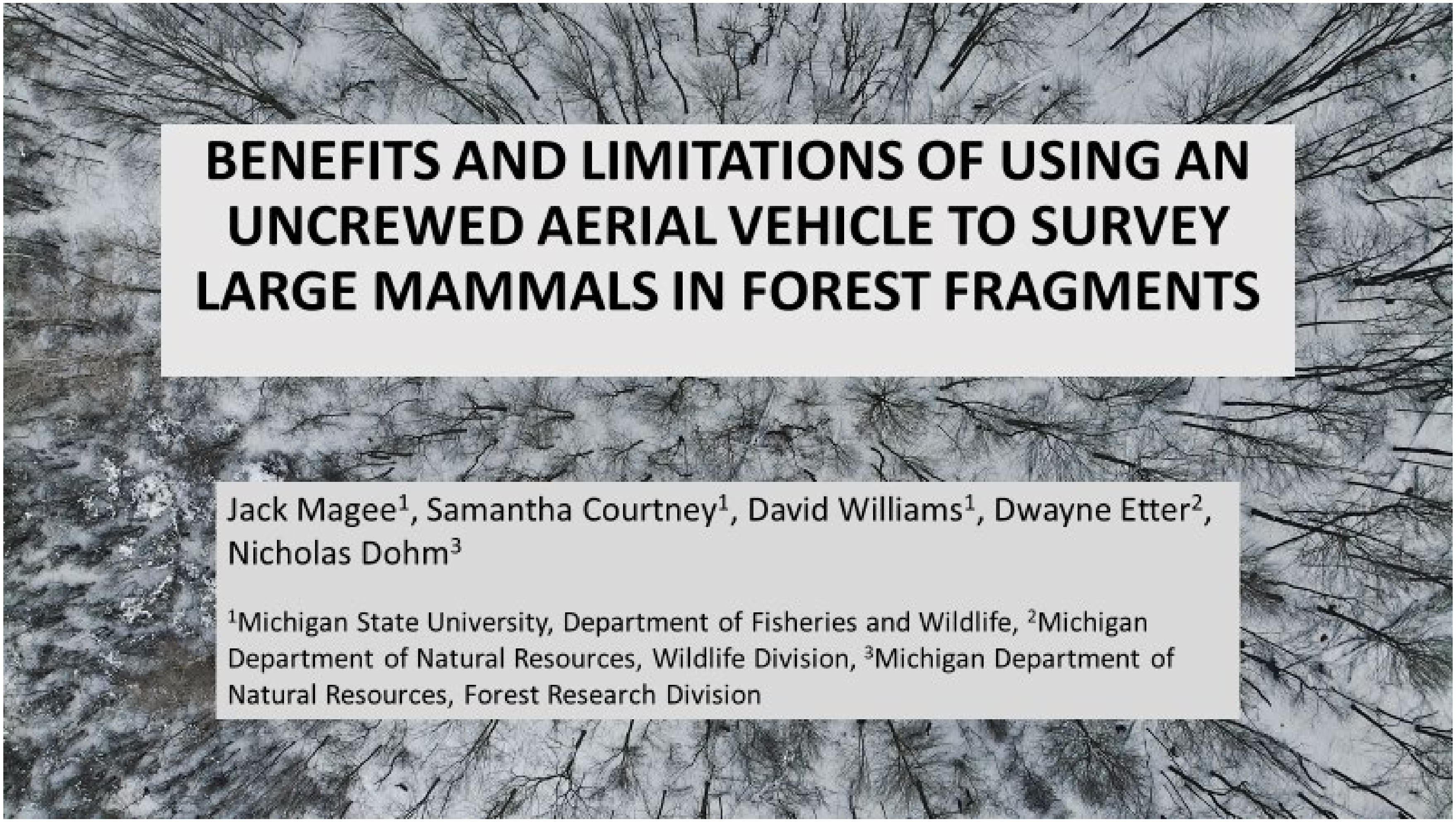
Questions? Email me! Jessica.duttenhefner@ndsu.edu

BACKGROUND ♦ OBJECTIVE ♦ METHODS ♦ RESULTS ♦ SUMMARY

Benefits and Limitations of Using an Uncrewed Aerial Vehicle to Survey Large Mammals in Forest Fragments

Jack Magee[1], Samantha Courtney[2], David Williams[1], Dwayne Etter[2], and Nicholas Dohn[3]
[1]Department of Fisheries and Wildlife, Michigan State University, mageejac@msu.edu
[2] Wildlife Division, Michigan Department of Natural Resources
[3] Forest Research Division. Michigan Department of Natural Resources

Animals that occupy wooded habitats are not easily detected from the ground using traditional sampling methods and in response many wildlife agencies are utilizing aerial survey techniques to estimate abundance. Collecting data from fixed wing aircraft with onboard observers has economical and logistical constraints that are not compatible with surveying at smaller scales. We will present on the benefits and challenges of using a small uncrewed aircraft vehicle (sUAV) to obtain high resolution imagery of white-tailed deer for winter aerial surveys in deciduous forest fragments. Compared to detection probabilities of other methods such as fixed-wing aircraft or camera trapping, surveys with sUAVs can improve the precision of abundance estimates. Using this approach can also provide auxiliary data such as group spacing and group size but there are unique data processing challenges with mapping in forested habitats. We found when sampling at low altitudes that the homogeneity of tree limbs along with the radial displacement of tall trees produced data that were difficult for mapping software to orthorectify. Sampling at a higher altitude reduces resolution and is limited by federal regulations, while reducing altitude is limited by the flight response of target animals and the ability to maintain a visual line of sight to the sUAV. We aim to design an optimal flight plan and survey protocols while addressing the challenges of existing mapping software to detect deer. We discuss potential impacts of these challenges for abundance estimation and efforts to quantify the dispersion of deer within and among groups.

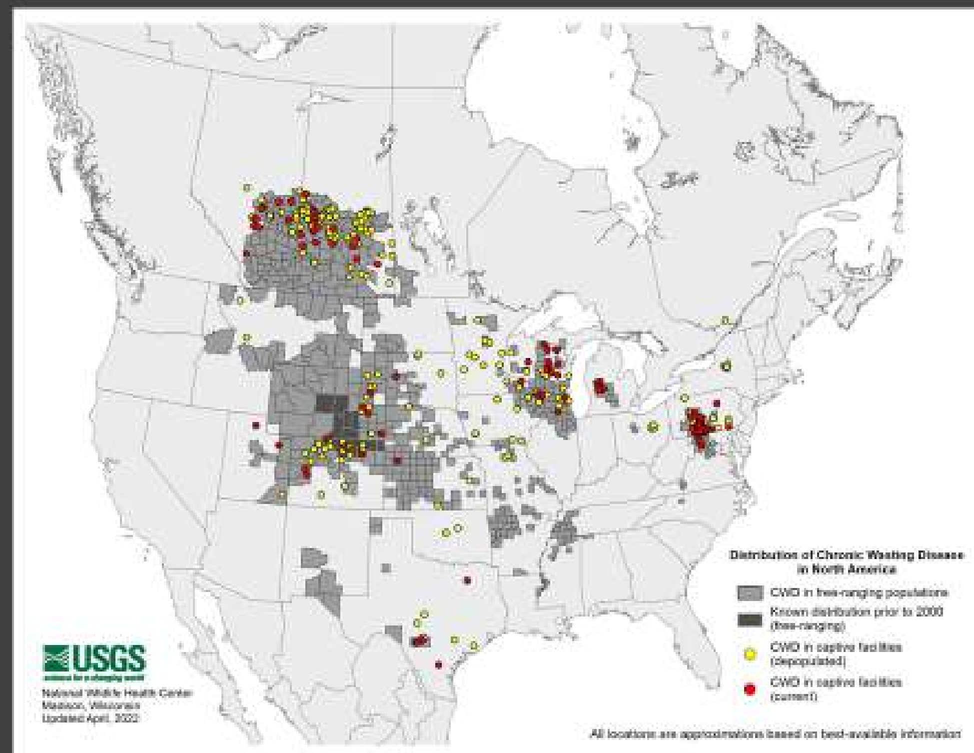

BENEFITS AND LIMITATIONS OF USING AN UNCREWED AERIAL VEHICLE TO SURVEY LARGE MAMMALS IN FOREST FRAGMENTS
Jack Magee[1], Samantha Courtney[1], David Williams[1], Dwayne Etter[2], Nicholas Dohm[3]
[1]Michigan State University, Department of Fisheries and Wildlife, [2]Michigan Department of Natural Resources, Wildlife Division, [3]Michigan Department of Natural Resources, Forest Research Division

Surveying Forest Fragments

- Increased fragmentation in forested landscapes worldwide
- Mosaic landscapes can concentrate animals in clusters that are not normally distributed
- Management implications for threatened and game species
- Detection with traditional methods is difficult in wooded habitats

Objectives

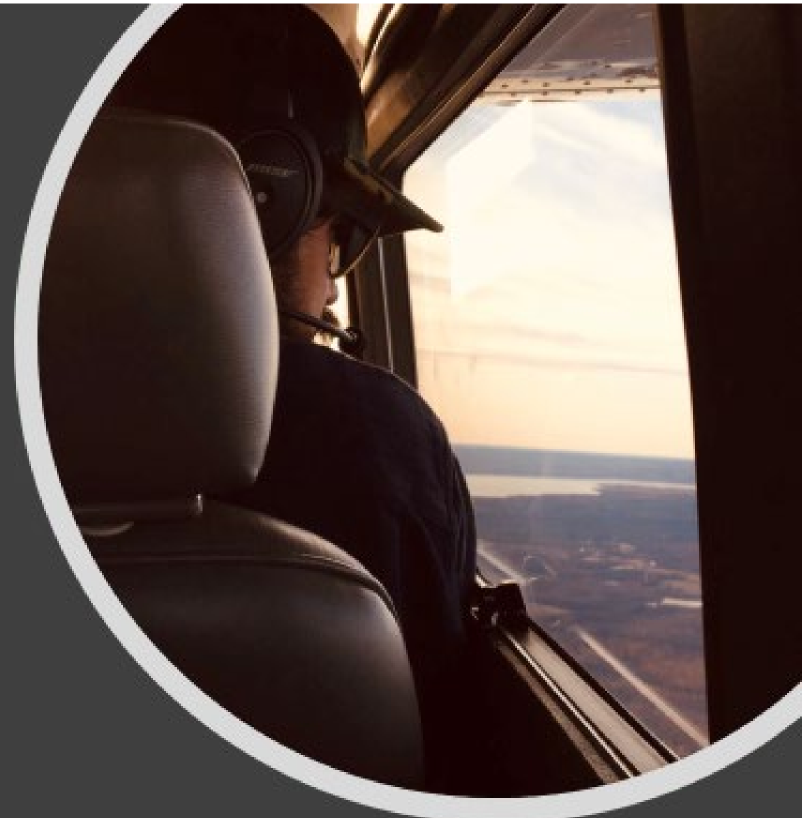
- Understand the potential for chronic wasting disease transmission (CWD)
- Improve detection probability of white-tailed deer in wooded habitats
- Provide data on deer congregations and predictive factors
- Improve the performance of agent-based models of chronic wasting disease transmission




Ground-Based Surveys
• Road-based distance sampling has limited detection in wooded areas
• Low population densities can result in low detection probabilities
• Fecal counts, genetic sampling and camera trap surveys are labor intensive, time consuming and expensive

Traditional Aerial Surveys

- Hazard risk to onboard personnel
- Expensive
- Better suited for larger spatial scales
- Negative influence on animal behavior
- Real-time observations are non-reviewable

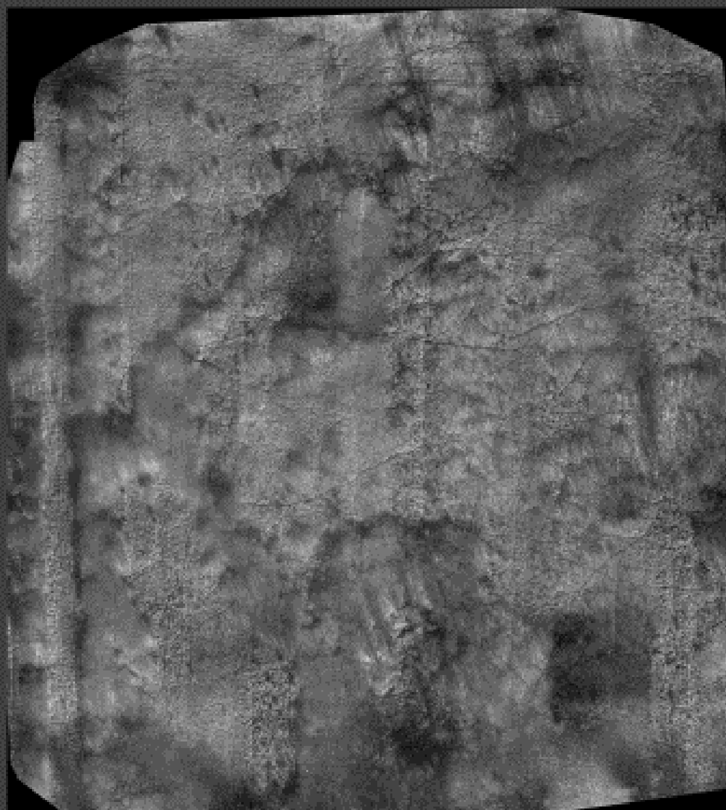


Flight Restrictions

- Flight ceiling ≤ 400 ft
- Line-of-sight limited by trees
- Requires a licensed pilot

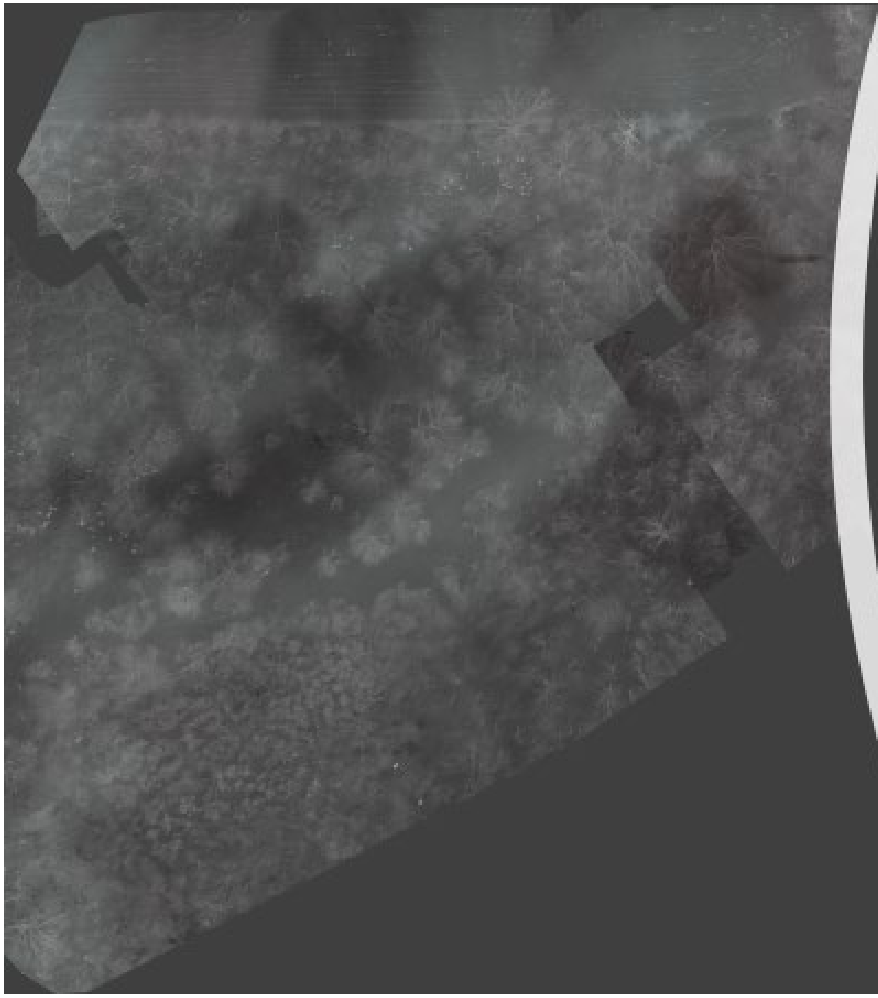
Flight Limitations

- Limited battery life
- Weather dependent



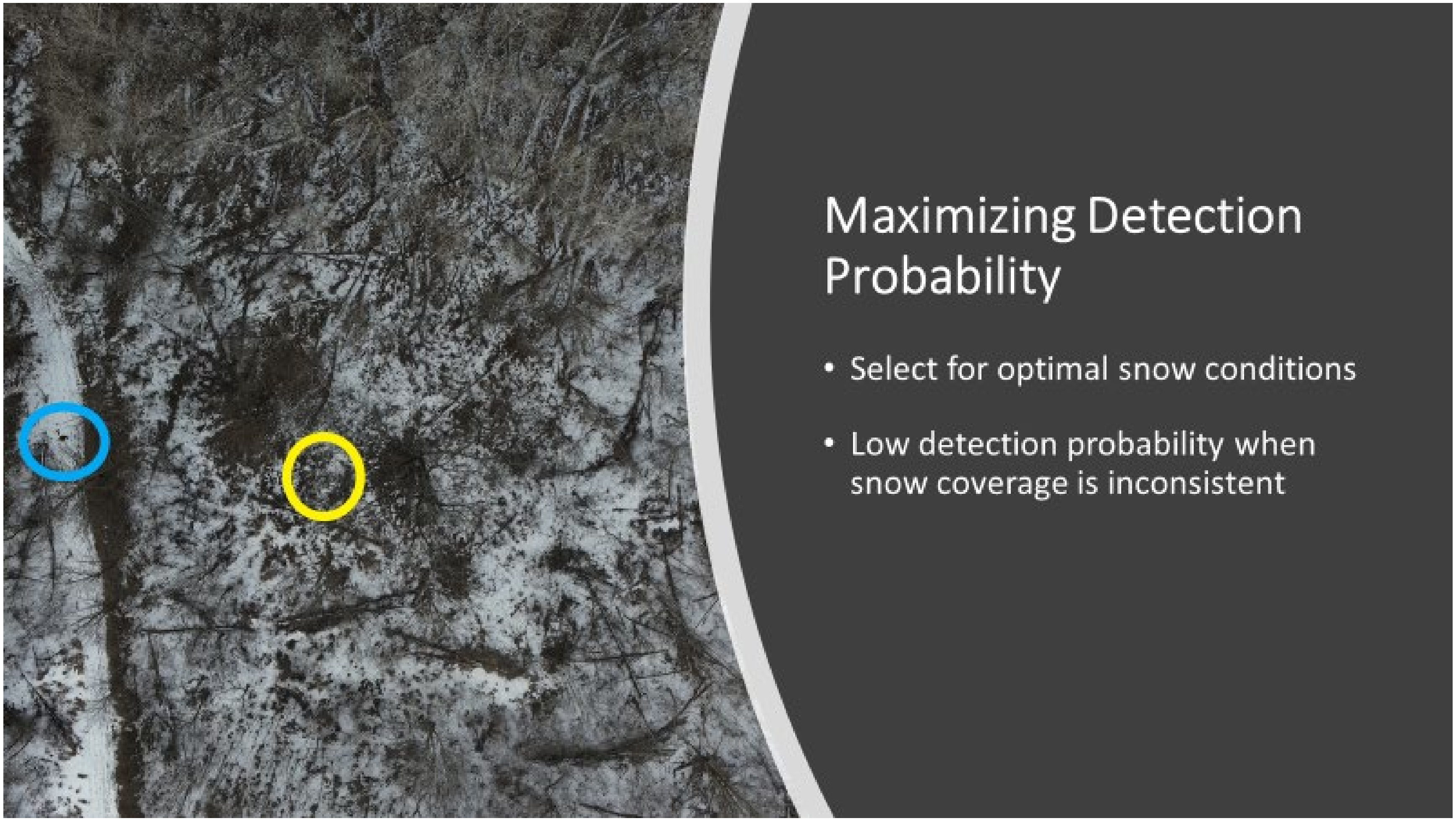
Initial Approach

- DJI Matrice 210 v2 with a Zenmuse XT camera
- Collect overlapping thermal imagery without control points to produce reviewable orthomosaics
- Estimate local abundance and identify congregation areas and attributes
- Sample areas ranged from 18-52 acres



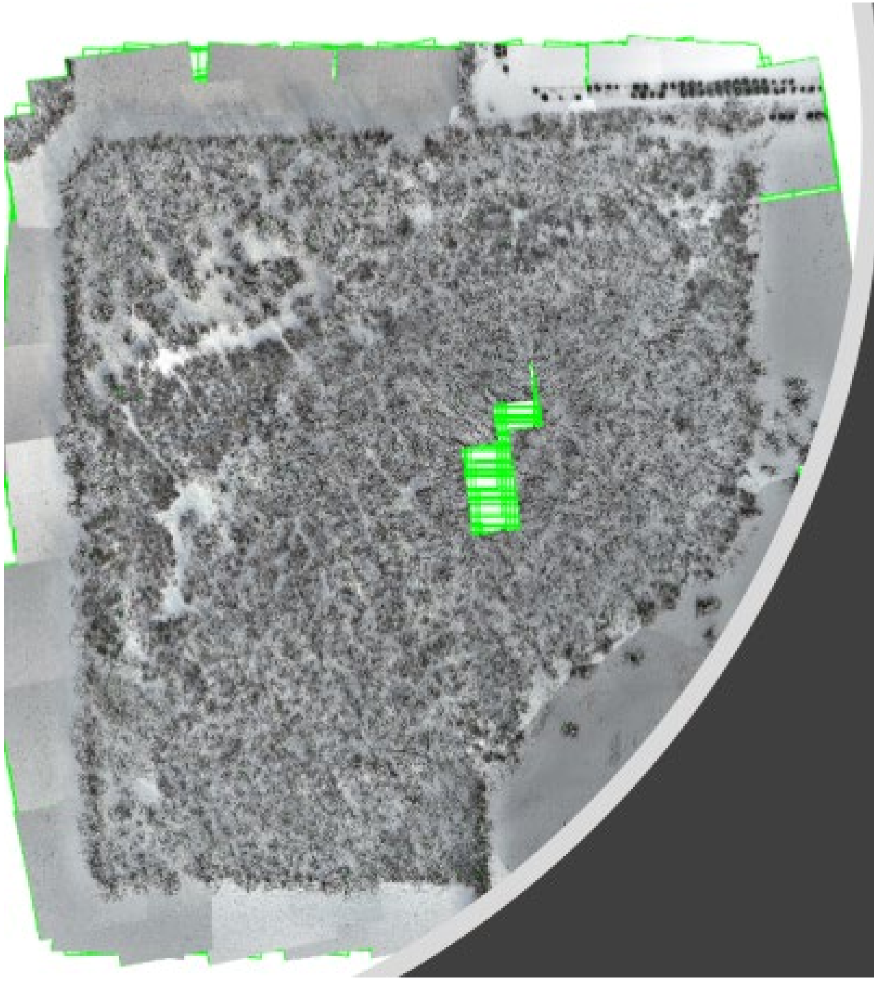
Results of Thermal Imagery

- Thermal imagery failed to orthorectify with Pix4D software
- Secondary high resolution RGB imagery offered promising alternative


Maximizing Detection Probability
• Select for optimal snow conditions
• Low detection probability when snow coverage is inconsistent

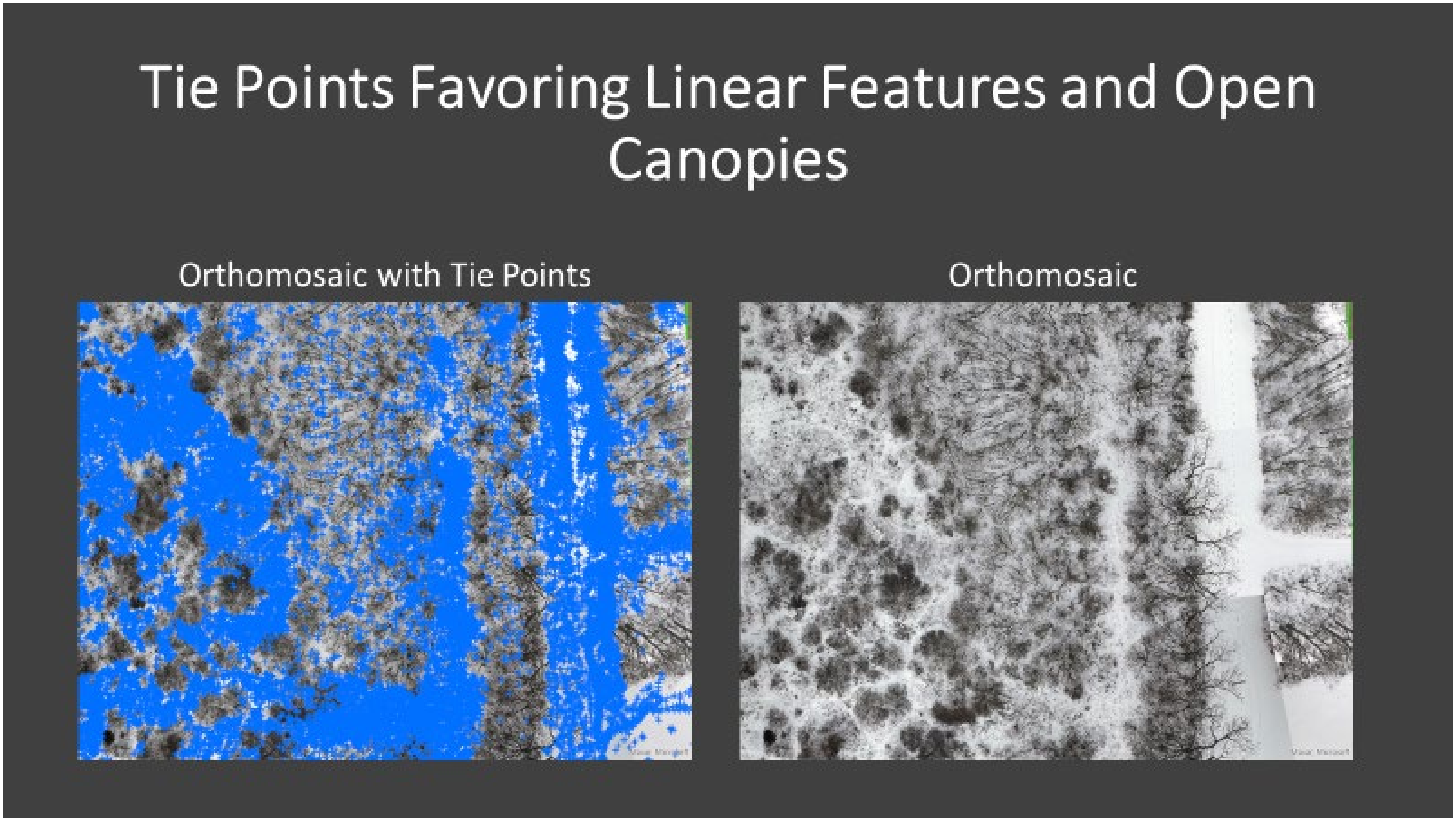
Secondary Approach

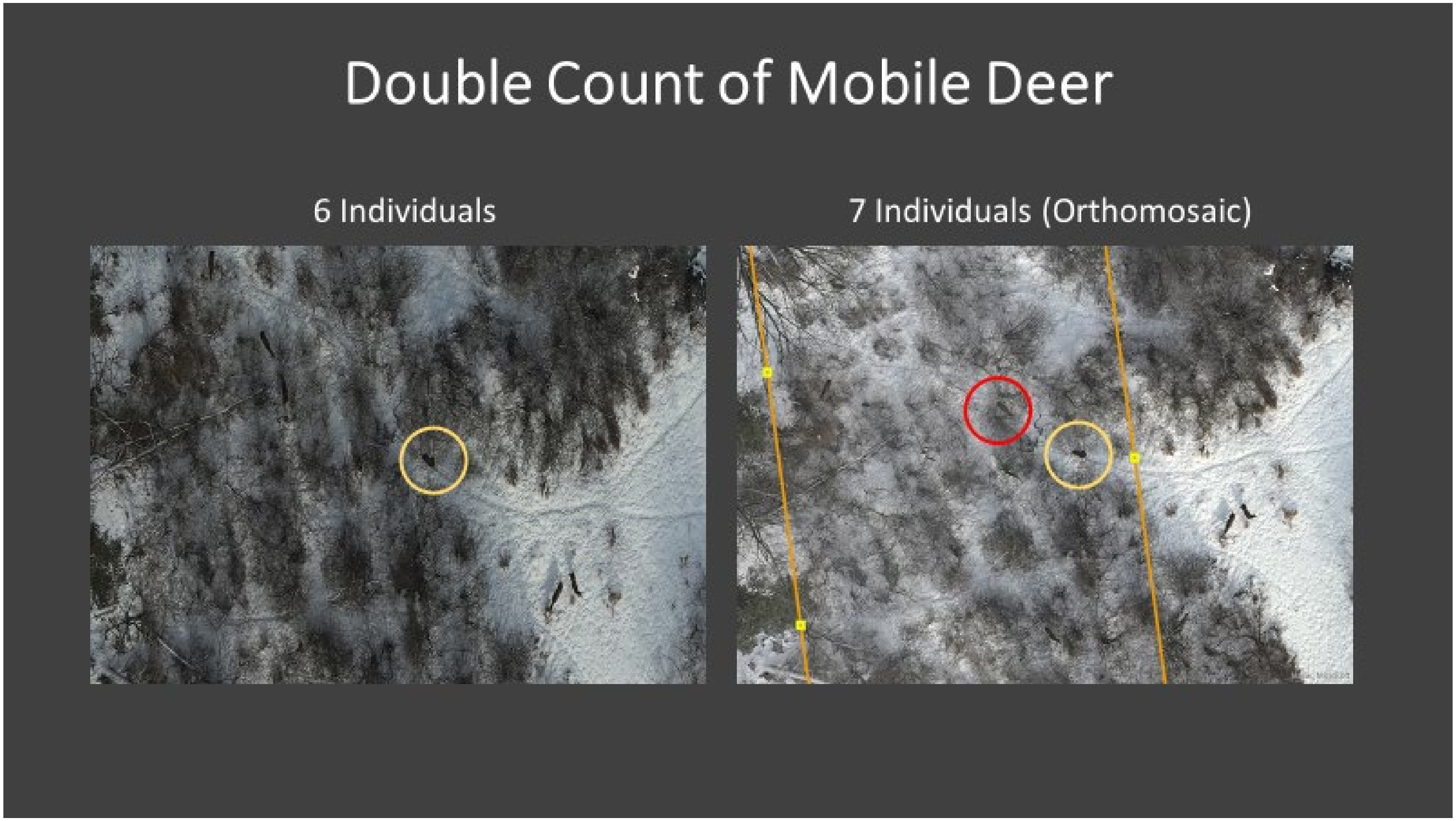
- Conduct surveys after snow deposition of ≥ 2 inches
- DJI Matrice 300 with Zenmuse P1 35mm camera
- Flight height of 100 meters AGL
- Resampled forest fragments



Results of High Resolution RGB imagery

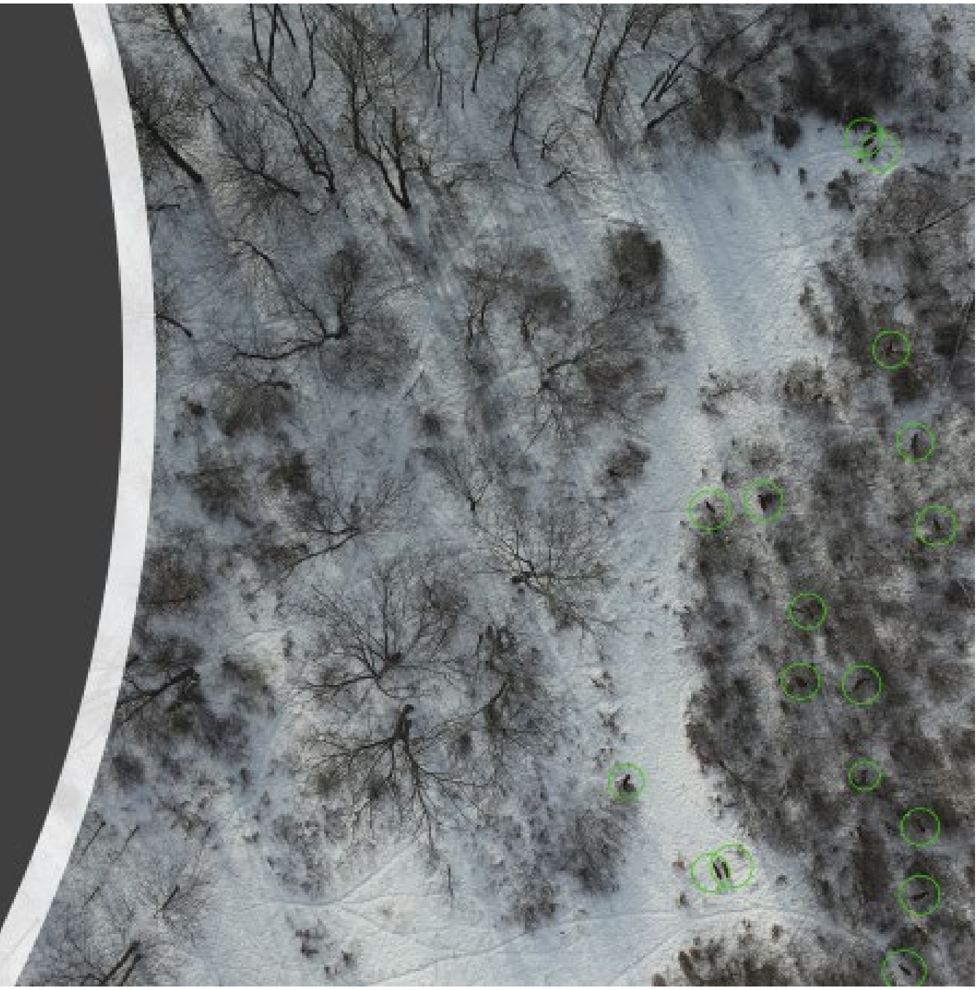
- High resolution imagery failed to orthorectify in areas with highest concentrations of mature deciduous trees
- Review of imagery between successive passes indicated behavioral response
- Individual deer that were moving were plotted more than once in orthomosaic


Tie Points Favoring Linear Features and Open Canopies
Orthomosaic with Tie Points
Orthomosaic


Double Count of Mobile Deer
6 Individuals
7 Individuals (Orthomosaic)

Value of High-Resolution Imagery

- Deer movement in orthomosaics
  - Precision error
  - Availability error
- Detection probability from individual photos
  - 20 photos
  - 3 observers
  - 3 minutes/photo
  - Detection probability: **0.936**



Discussion

- Modify sample design
- Behavioral response varies by species and habitat
- Increase height
- Change equipment
- Non-overlapping transects
- Continue refining approach

Discussion Continued

- Chronic wasting disease distribution is expanding
- Improve localized disease management
- Applications for other species and diseases
- Technological advancements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Evaluation of UAS Surveys for Ungulates in South Texas Rangelands

Aaron Foley[1], Jesse Exum[1], Randy DeYoung[1], David Hewitt[1], Jeremy Baumgardt[1], Humberto Perotto-Baldivieso[1], and Mike Page[1], and Mickey Hellickson[2]
[1]Caesar Kleberg Wildlife Research Institute, Texas A&M University-Kingsville; Aaron.Foley@tamuk.edu
[2]Orion Wildlife Management Services

Drones have emerged as another tool in the toolbox of wildlife research and management. One highly anticipated application of drones is to survey wildlife. Previous drone-based population estimates assume no visibility bias; thus, uncorrected counts are often reported. We used distance sampling techniques to evaluate detection probabilities (p) of large herbivores from a drone platform in South Texas, USA. We used quadcopters equipped with thermal video cameras to conduct repeated daytime surveys on 5 study sites with varying habitat characteristics during February–April 2020. Drones were programmed to fly fixed-width transects at 24 km/hr, 37 m above ground level, which generated a transect 57 m wide. Most sites had $p < 1$ indicating that animals were missed. Sites comprised of flat terrain with interspersed brush mottes had $p = 0.50–0.64$; p appreciably declined at 20–25 m from the transect. A site with arroyos had $p = 1.0$ but number of detections were very low indicating that the inability of drone to follow contours affected thermal contrasts. The last site had a negative-skewed distance distribution because the 80% herbaceous cover (vs 28–45% herbaceous cover in other sites) caused severe solar reflectance in the center of the footage. Overall, our results indicate that probability of detection was not uniform during daytime thermal surveys; therefore, uncorrected counts should be avoided. Further, the use of distance sampling may result in more accurate population estimates but should be evaluated for specific vegetation and terrain characteristics.

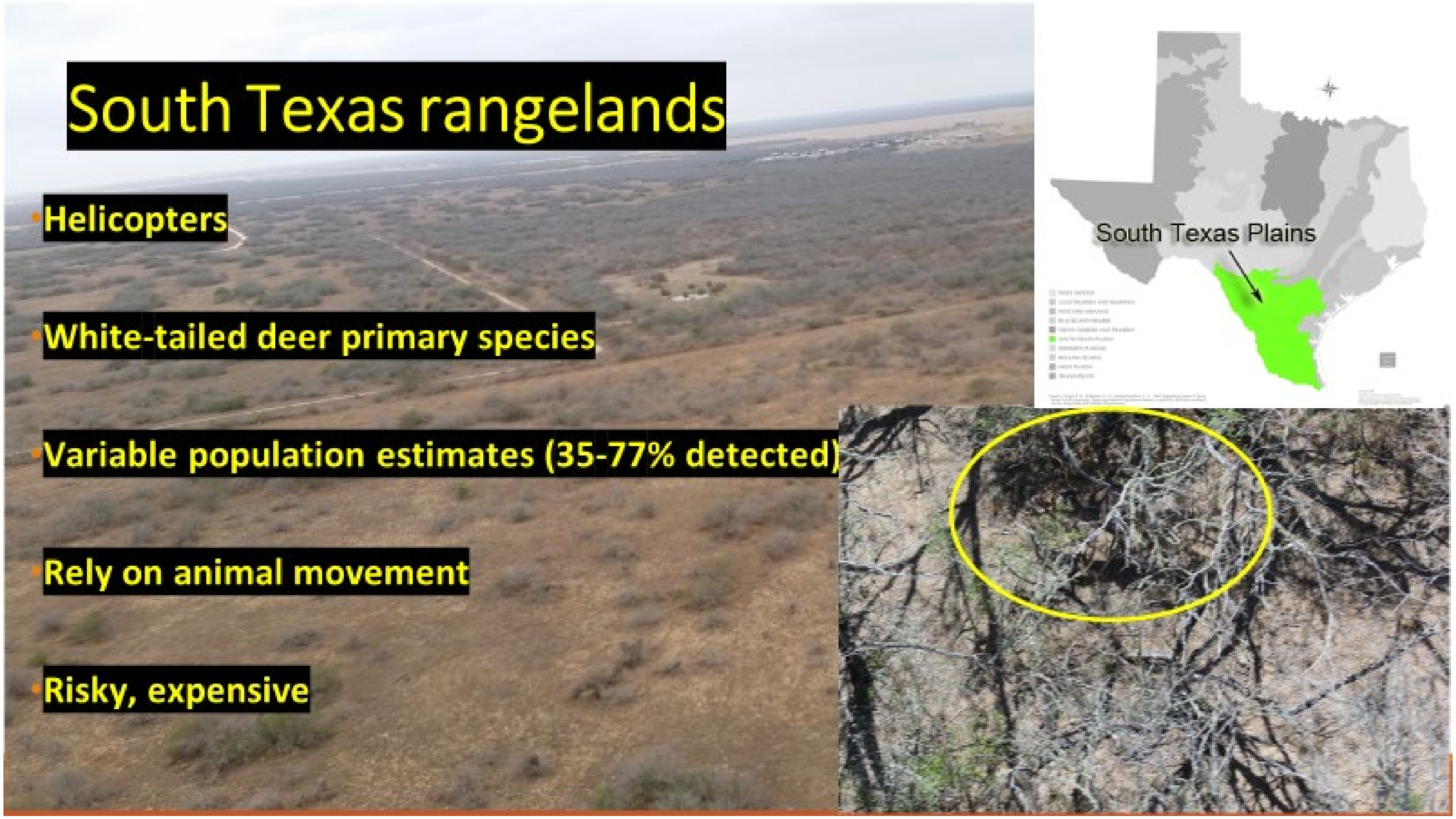
Evaluation of UAS surveys for ungulates in South Texas rangelands

AARON FOLEY, JESSE EXUM, RANDY DEYOUNG, DAVID HEWITT, JEREMY BAUMGARDT, HUMBERTO PEROTTO-BALDIVIESO, MIKE PAGE, AND MICKEY HELLICKSON

Aerial Surveys

Common for surveying populations (ungulates, cetaceans, birds, etc.)

Valuable for estimating population size/density relative to management goals


South Texas rangelands
Helicopters
White-tailed deer primary species
Variable population estimates (35-77% detected)
Rely on animal movement
Risky, expensive
South Texas Plains

UAS as an alternative (improved) option?

Need a thorough evaluation

Detection probability?

Precision of density estimate?

Repeatability?

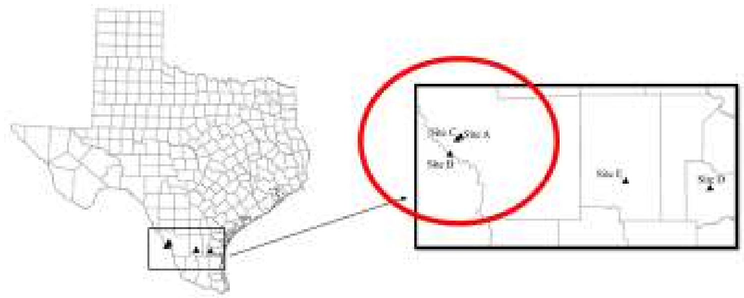
Comparable with other survey methods?

Objective 1

Evaluate effects of different habitats on *p*

2 surveys on each of 3 sites

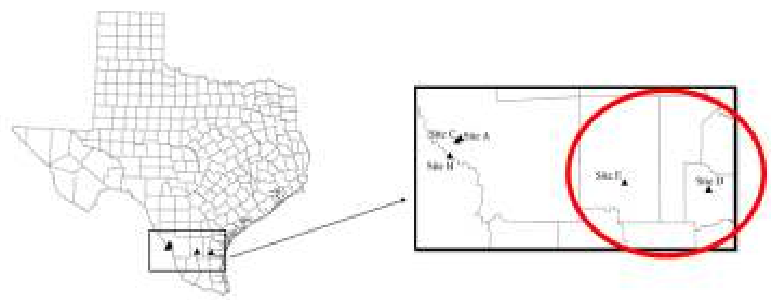
- Grassy and flat
- Brushy and flat
- Brushy and hilly



Objective 2:

Precision, repeatability, comparison to other estimators

- Repeated UAS surveys on 2 sites
- Spotlight count (distance sampling)
- Helicopter survey (corrected strip count)
  - DeYoung et al. 1989 WSB 17:275-279
- Baited camera survey (Jacobson's method)
  - Jacobson et al. 1997 WSB 25:547-556



Methods

DJI Matrice 210 Quadcopter with Zenmuse XT2 camera

Focused on thermal footage

Daylight, post-sunrise

Feb-Apr 2020

Methods

Protocol development

Short, one transect flights over deer

Heights: 24m, 30m, 37m

Speeds: 4.5m/s, 6.7m/s

Downward camera angles: 15°, 30°

Simple rating system of clarity of target animals

Test Flight Evaluation

Reviewer: ________________

Please review each video and rank detectable objects (focus: drone cases by cones) on a simple scale of blurriness described below for each of the thermal and optical versions of the videos. Feel free to add any notes regarding the footage. Thank you!

Blurriness scale:
1: Sharp
2: Middle-ground but still identifiable
3: Blurry

Test Video	Thermal	Notes
1		
2		
3		
4		
5		
6		
7		
8		
9		
10		
11		
12		
13		
14		
15		
16		

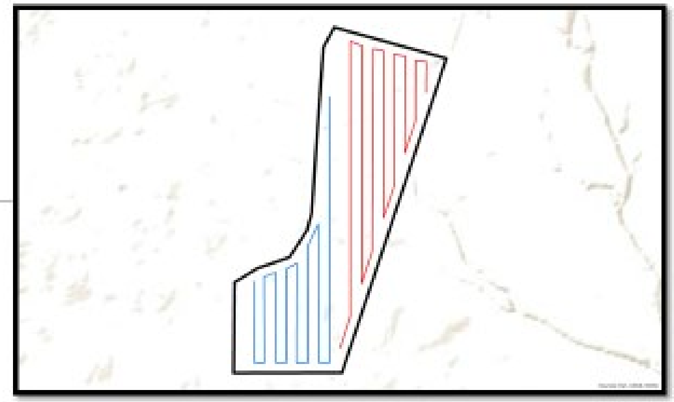
Methods

36.6 m AGL, 6.7 m/s, 20 degree camera

57 m swath

200 ha survey blocks

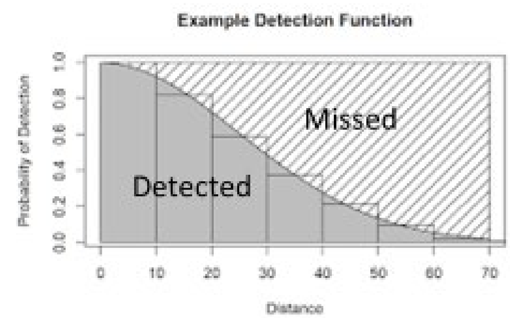
Fixed width transects, 50% coverage



Methods

Distance sampling

- Probability of detection (*p*)
- Precision of density estimate (CV)
- Population estimate with measure of variance (SE, CI)



Methods

Distance sampling

Minimum 60-80 detections recommended (Buckland et al. 2015)

Pooled surveys to meet minimum of 60 detections (max 3 surveys)

Example: 3 surveys conducted

Pooled surveys 1 + 2

Pooled surveys 2 + 3

Pooled surveys 1 + 3

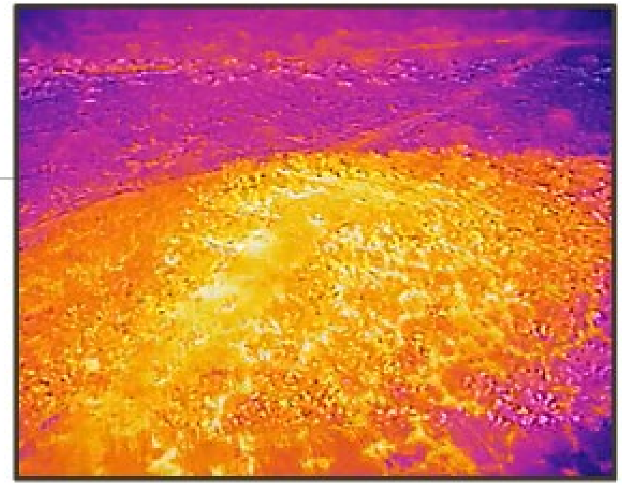
Pooled surveys 1 + 2 + 3

Results (Habitat/terrain)

Flat grassland

2 surveys pooled (22 detections)

Results (Habitat/terrain)



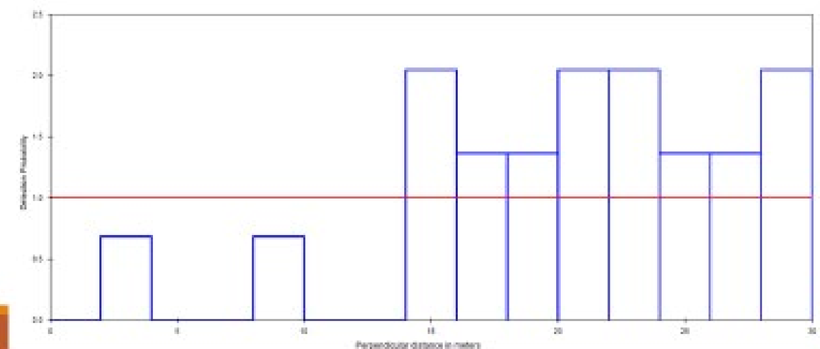
Flat grassland

2 surveys pooled (22 detections)

Missed animals near the transect

Solar reflectance in center of screen

"spotlight effect"



Results (Habitat/terrain)

Flat and brushy

Independent (109 and 63 detections)

Results (Habitat/terrain)

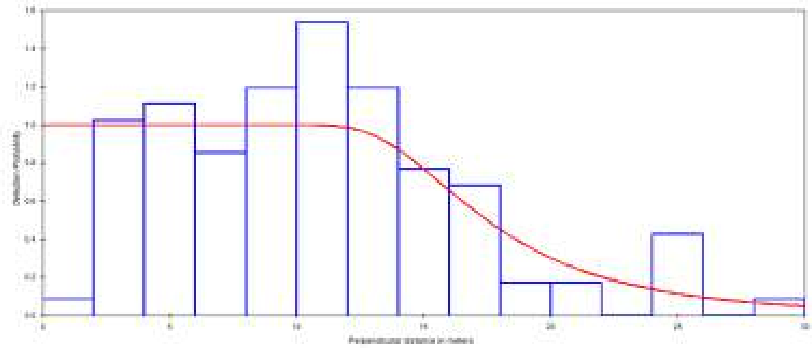
Flat and brushy

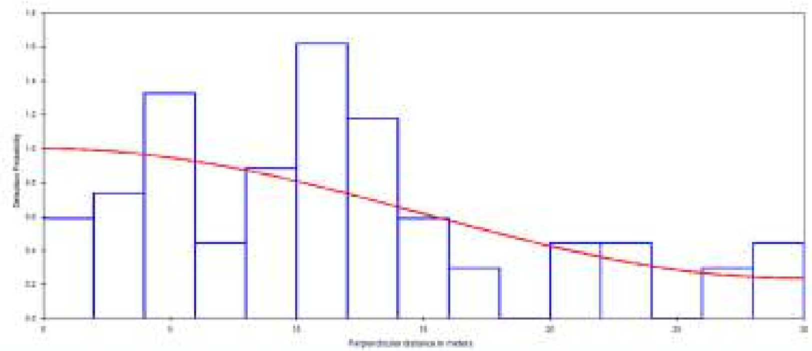
Independent (109 and 63 detections)

p = 0.62 and 0.62

Decaying detection function

Indicates visibility bias



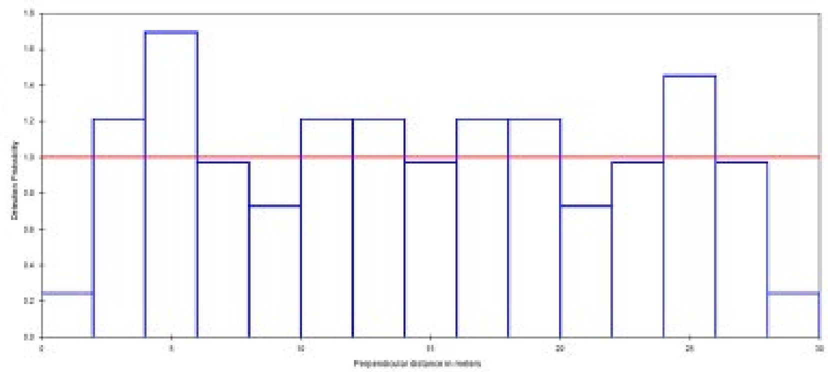


Results (Habitat/terrain)

Brushy and hilly

2 surveys pooled (62 detections)

Results (Habitat/terrain)



Brushy and hilly

2 surveys pooled (62 detections)

p = 1.00

64% lower detections than flat/brushy site

Varying “true” AGL = different thermal contrasts

Misleading detection function

Results (Repeated surveys)

Brushy and flat

10 pooled surveys with ≥60 detections

Results (Repeated surveys)

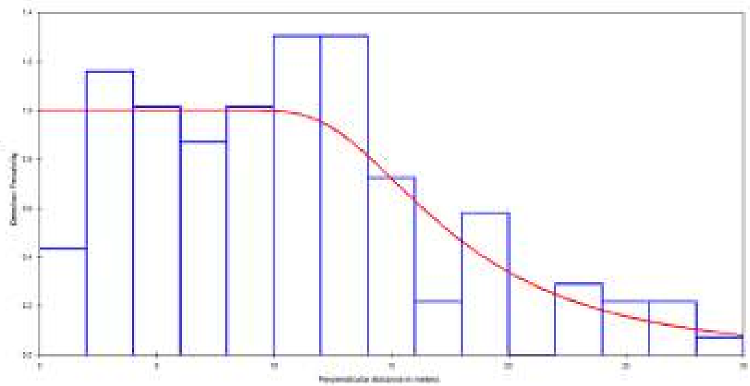
Brushy and flat

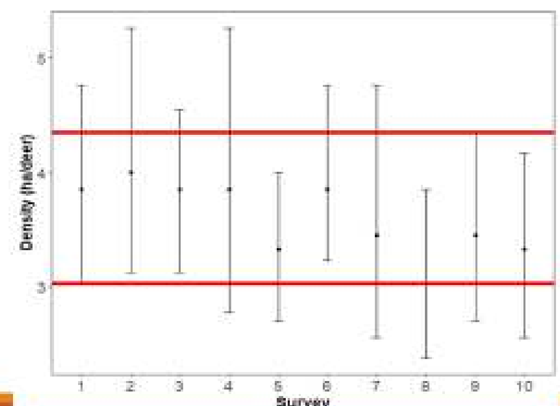
10 pooled surveys with ≥60 detections

p = 0.56-0.70

Each density estimate had CV of <20% ($\bar{x}$ = 11%)

Repeatable density estimates (9% CV)

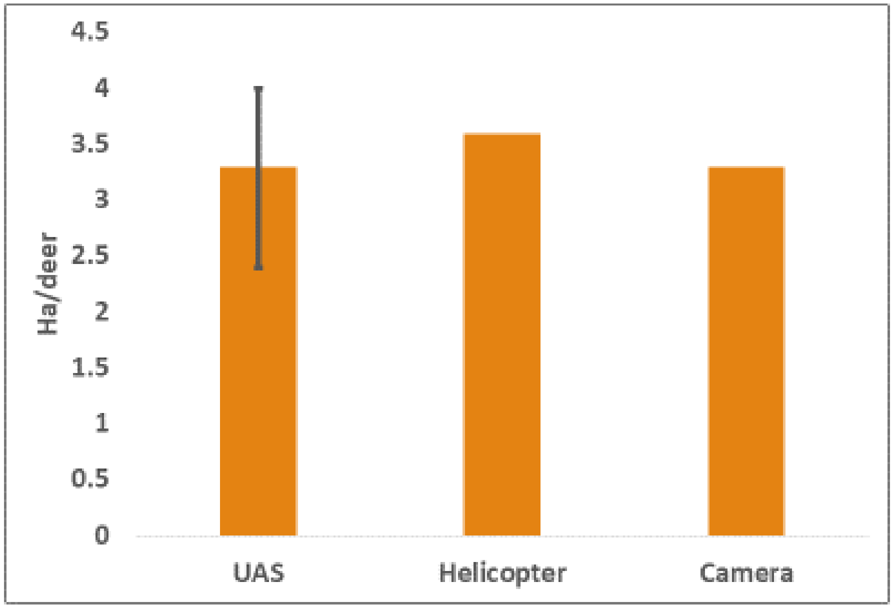




Results (Repeated surveys)

Brushy and flat

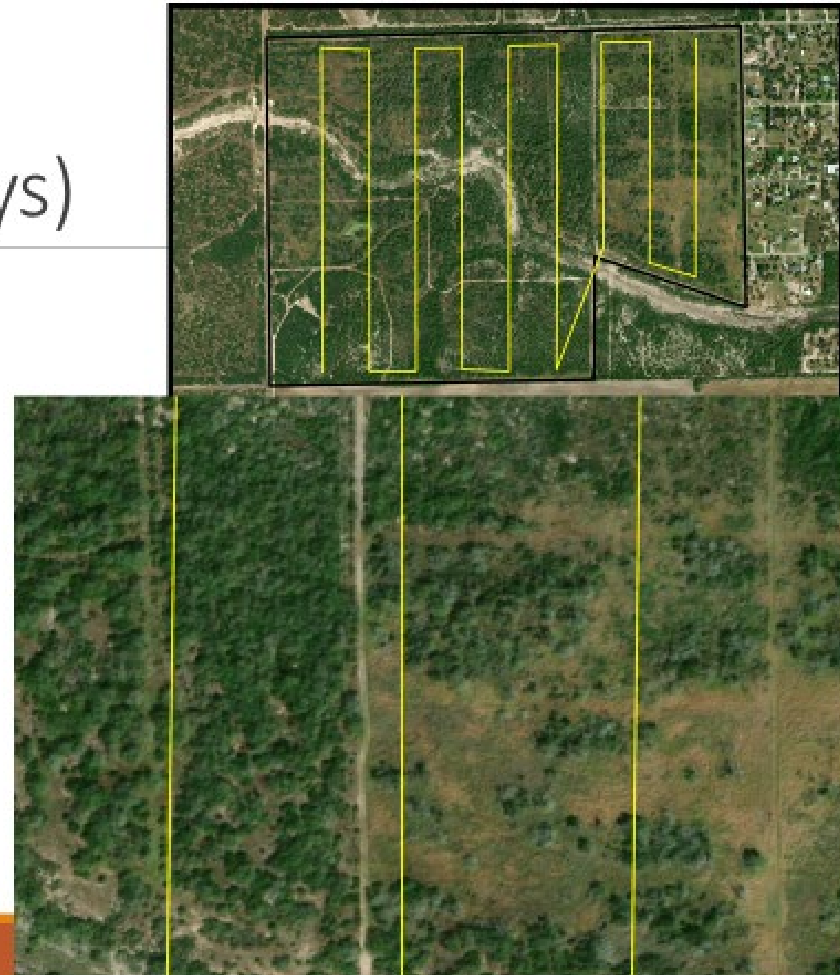
Comparable with other estimators



Results (Repeated surveys)

Brushy and flat

47 pooled surveys with ≥60 detections



Results (Repeated surveys)

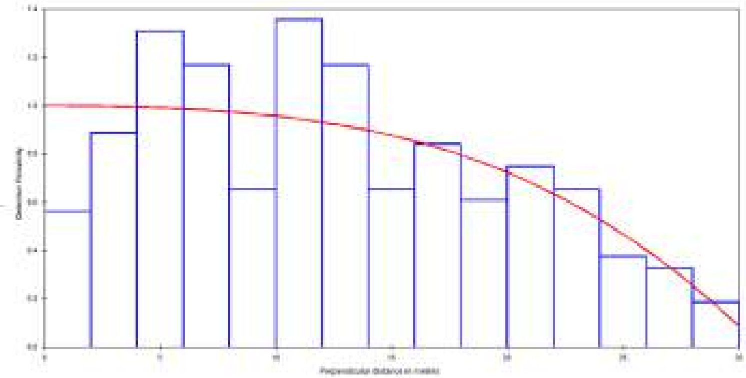
Brushy and flat

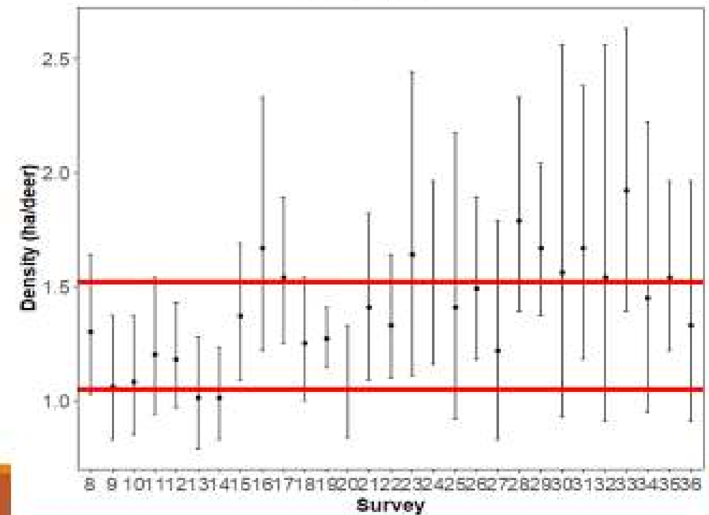
47 pooled surveys with ≥60 detections

p = 0.58-1.00 ($\bar{x}$ = 0.81)

77% surveys with <20% CV ($\bar{x}$ = 14%)

Repeatable density estimates (20% CV)

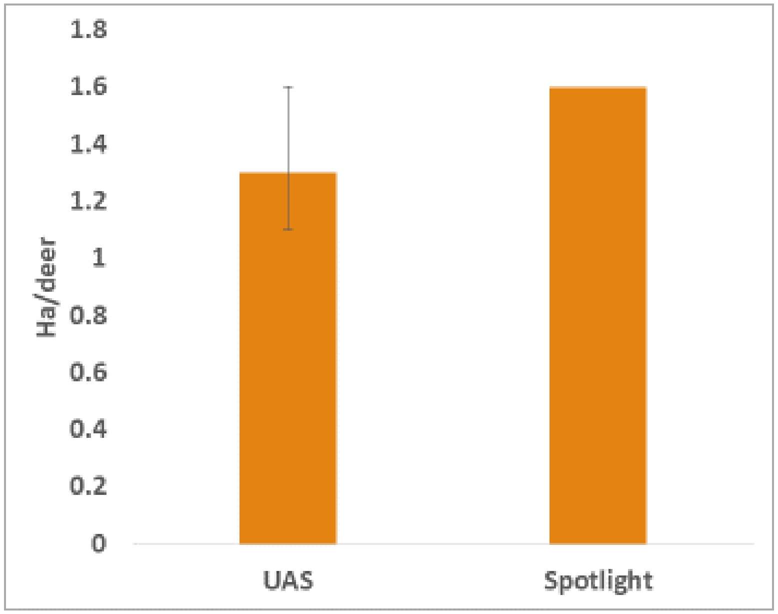




Results (Repeated surveys)

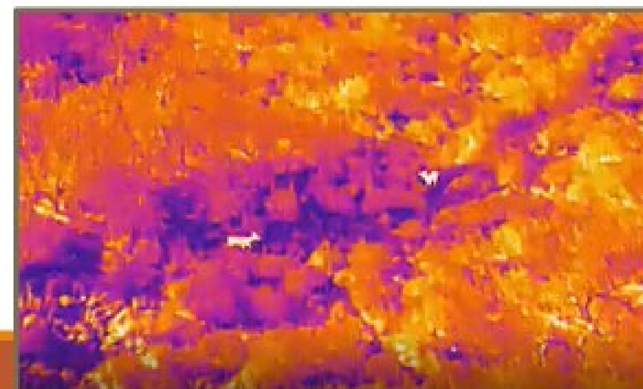
Brushy and flat

Comparable with spotlight surveys (*n* = 5)



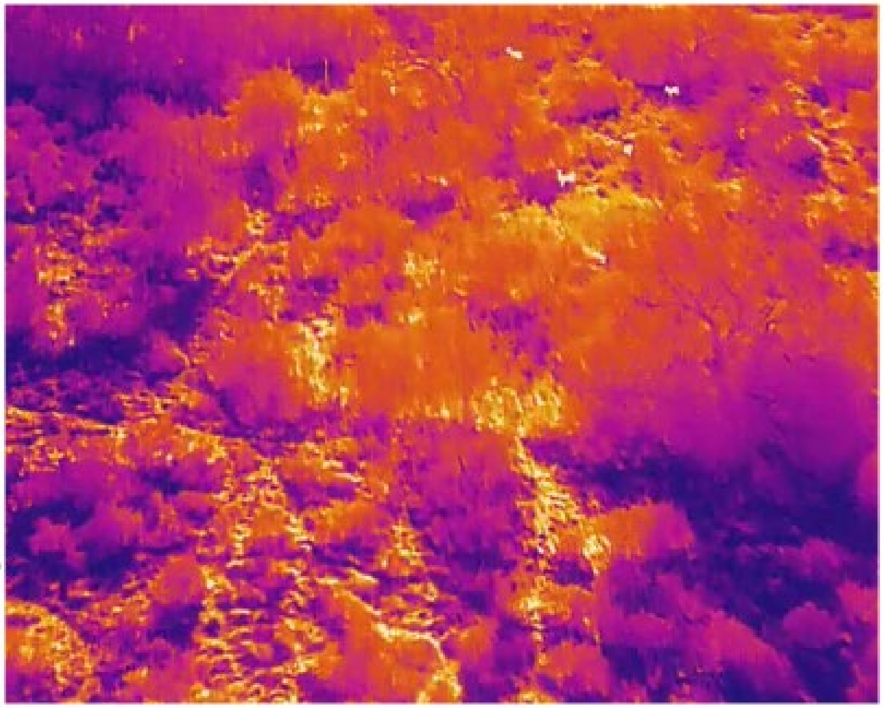
Summary

- Evidence that UAS can generate scientifically defensible population estimates
  - For WTD in South Texas in flat and brushy terrain
- Distance sampling methods useful for evaluation and accounting for visibility bias
- Critical to have *a priori* knowledge of population size or independent population estimator



Pros

- Does not rely on animal movement
- Higher p than helicopters
- More consistent population estimates



Cons

- Sex/age ratios unavailable
- Species ID ambiguous
- Temperature dependent (<21° C)
- Not "off-the-shelf"

Acknowledgments

DSC

GMD, Arroyo, Dolores-Needmore, Zacatosa, and Sweden ranches

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Rene Barrientos

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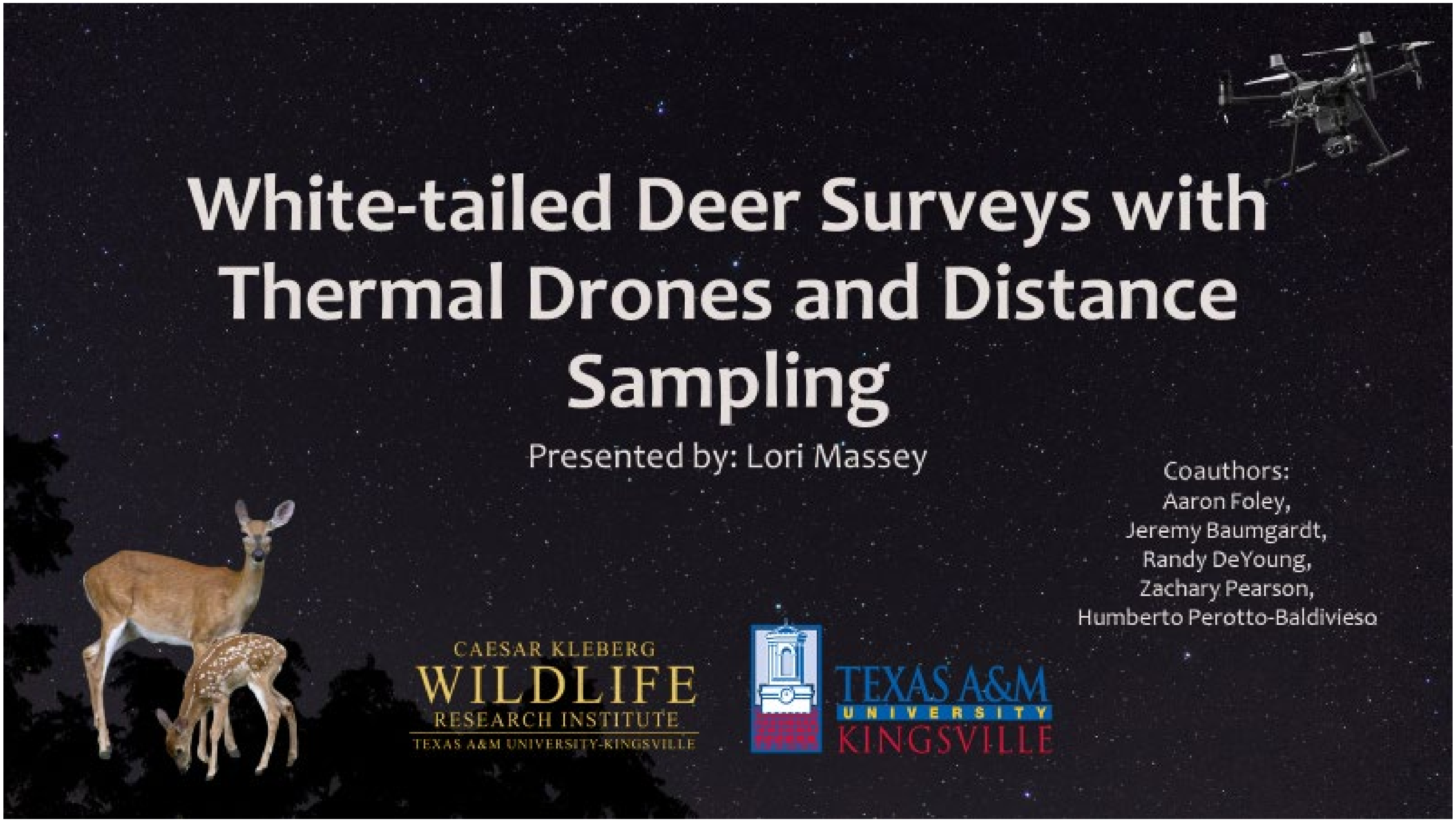
Mr. Phillip Plant

Quail Coalition of South Texas

White-tailed Deer Surveys with Thermal Drones and Distance Sampling

Lori Massey*, Aaron Foley*, Jeremy Baumgardt*, Randy DeYoung*, Zachary Pearson*, and Humberto Perotto-Baldivieso*
*Caesar Kleberg Wildlife Research Institute, Texas A&M University-Kingsville; lori.massey@students.tamuk.edu

Improvements in thermal infrared imaging and relaxation of Federal Aviation Administration (FAA) regulations provide new opportunities for drone-based wildlife surveys. Advances in thermal technology include isotherm capabilities, which highlights a range of temperatures and produces higher-contrast imagery. Additionally, previous surveys have been limited to daylight or twilight hours; recent changes in FAA drone regulations now allow for nighttime flights. Our goal was to evaluate nighttime surveys of white-tailed deer (*Odocoileus virginianus*) in South Texas using a drone equipped with a thermal camera programmed to search for specific temperature ranges. Our objectives were to 1) determine if nighttime surveys increased detection probabilities relative to daytime surveys, 2) whether isotherm technology improved number of detections relative to traditional thermal technology and 3) determine the effect of season on detection rates. We surveyed a 102-ha game-fenced property during February, April, and July 2022. Distance sampling analyses of the 3 surveys indicated that detection probability was <1, similar to daytime surveys. Using the isotherm setting did not significantly increase number of detections relative to traditional thermal technology. However, the isotherm allowed us to identify deer in warmer ambient temperatures (24°C) than traditional thermal technology (~21°C). Further, contrast between the deer and the background was noticeably better with isotherm vs traditional thermal. In terms of seasonality, detection rates vary due to changes in swath width most likely due to fluctuations in canopy cover. Overall, our results indicate that deer are missed during both daytime and nighttime surveys; incorporating distance sampling methods can improve accuracy of estimated population sizes by correcting for visibility bias. Additionally, matching isotherm settings to ambient temperatures allowed us to survey during temperatures previously thought to be too warm for ideal contrast.

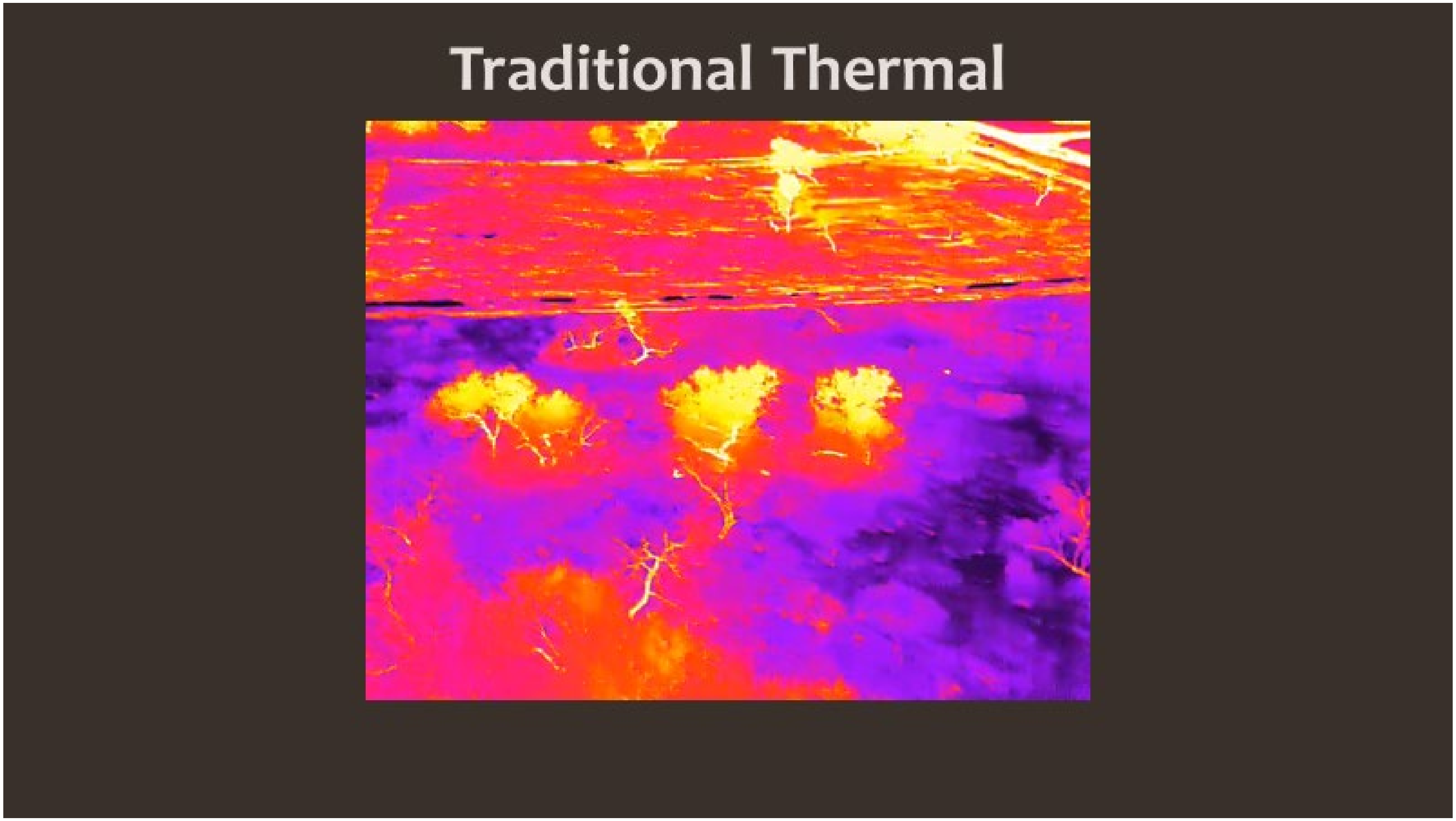

White-tailed Deer Surveys with Thermal Drones and Distance Sampling
Presented by: Lori Massey
Coauthors:
Aaron Foley,
Jeremy Baumgardt,
Randy DeYoung,
Zachary Pearson,
Humberto Perotto-Baldivieso
CAESAR KLEBERG
WILDLIFE
RESEARCH INSTITUTE
TEXAS A&M UNIVERSITY-KINGSVILLE
TEXAS A&M
UNIVERSITY
KINGSVILLE

Aerial Surveys

- Dangerous
- Expensive
- Rely on movement

Drones

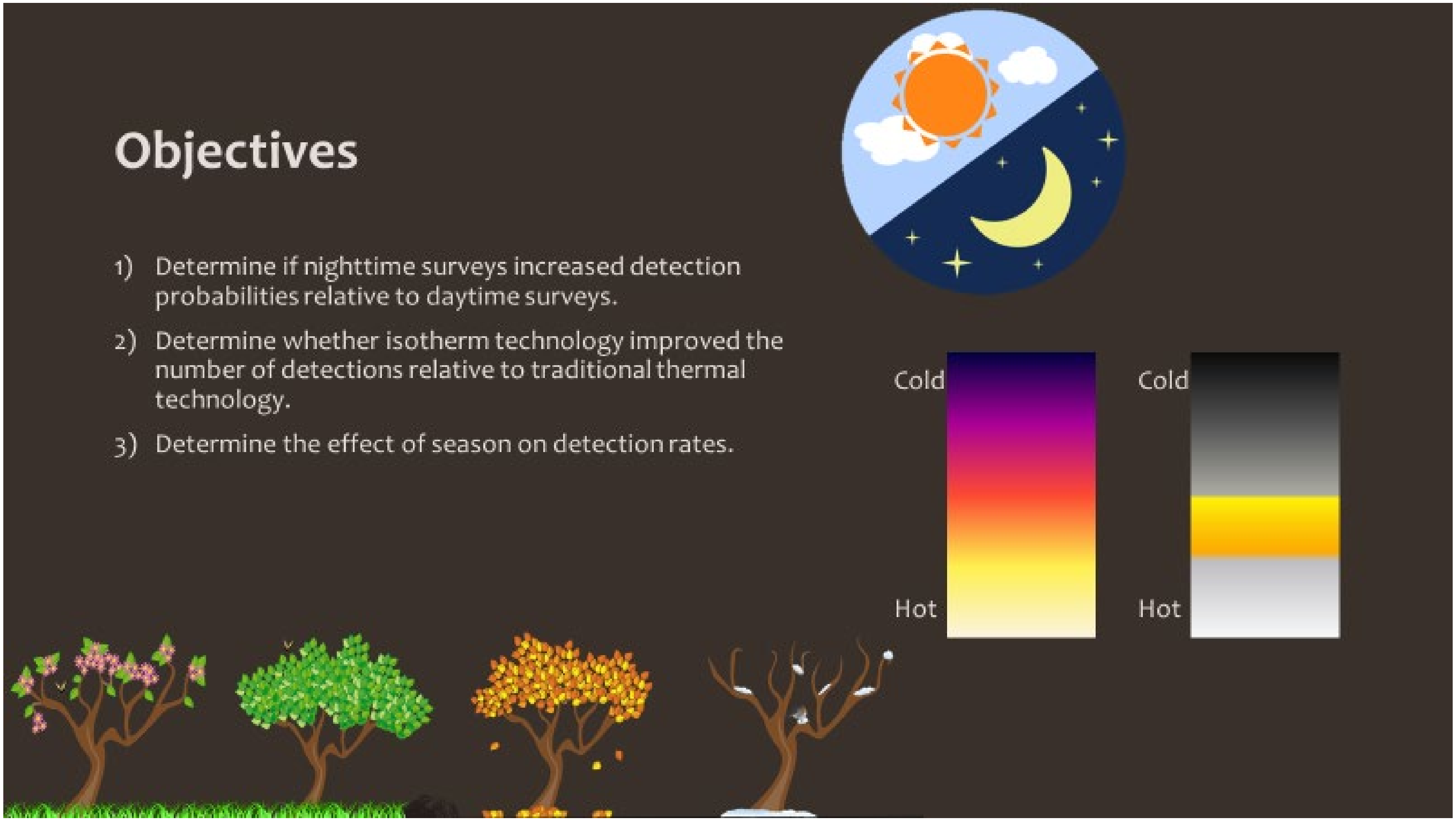
- Lower Risk
- Doesn’t rely on animal movement
- Nighttime

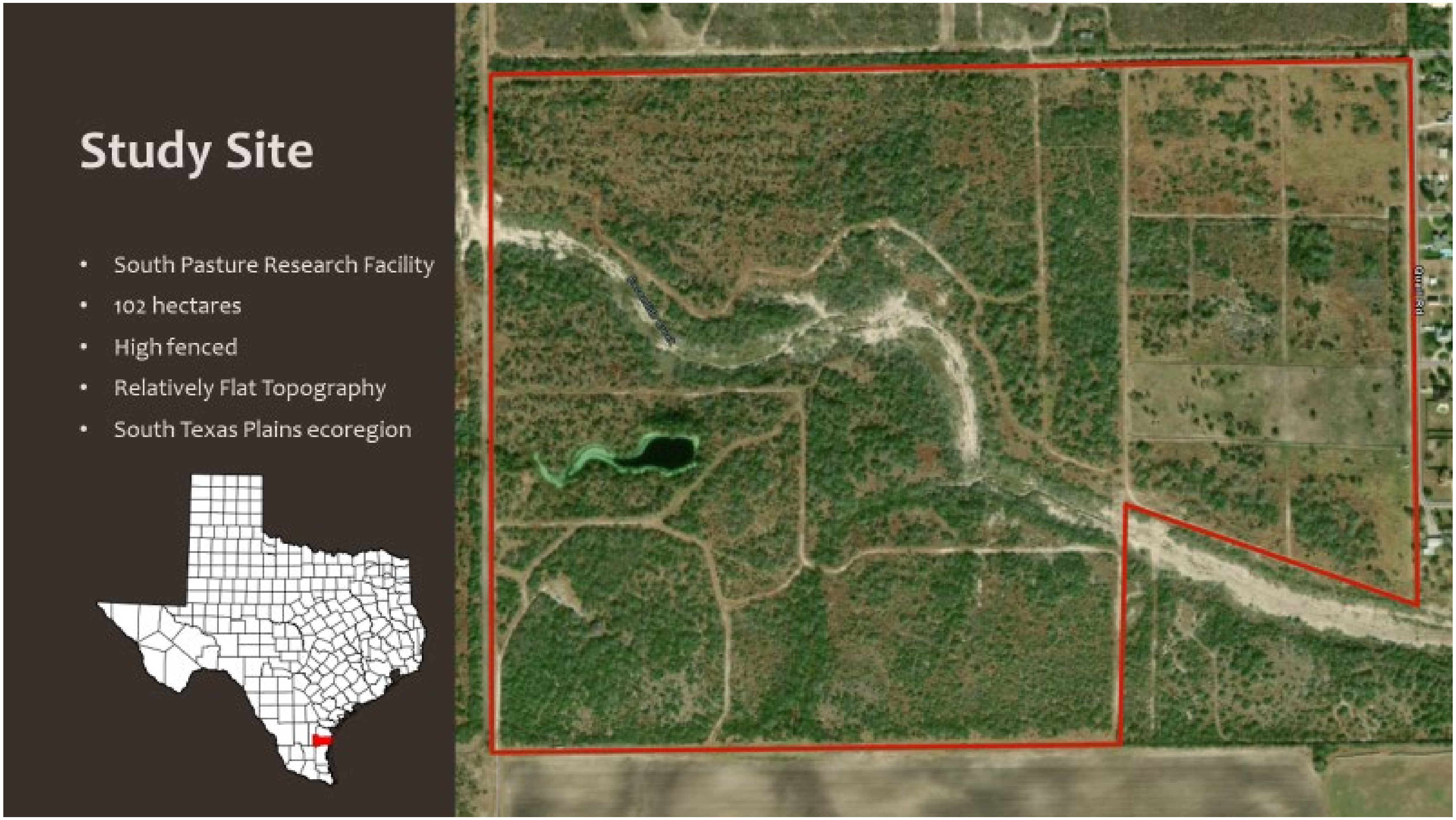

Traditional Thermal


Isotherm Thermal

Distance Sampling

- The probability of detecting an animal decreases as its distance from the observer increases.


Objectives
1) Determine if nighttime surveys increased detection probabilities relative to daytime surveys.
2) Determine whether isotherm technology improved the number of detections relative to traditional thermal technology.
3) Determine the effect of season on detection rates.
Cold
Hot
Cold
Hot


Study Site
• South Pasture Research Facility
• 102 hectares
• High fenced
• Relatively Flat Topography
• South Texas Plains ecoregion

Equipment

- DJI Matrice 210 RTK
- Zenmuse XT2
- Anti-Collision Lights

Pre Flight-Calibration

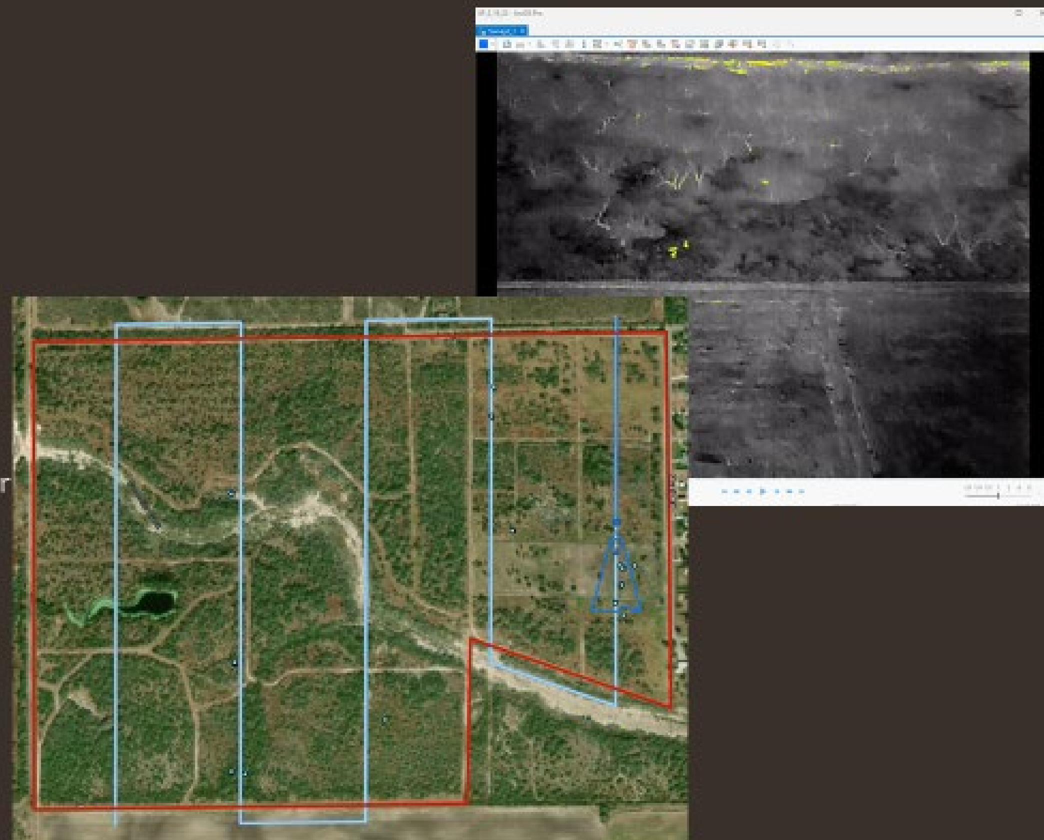
- CKWRI
  - Albert and Margaret Alkek Ungulate Research Facility
- Night before survey
- Isotherm Thresholds
  - Lower
  - Middle
  - Upper

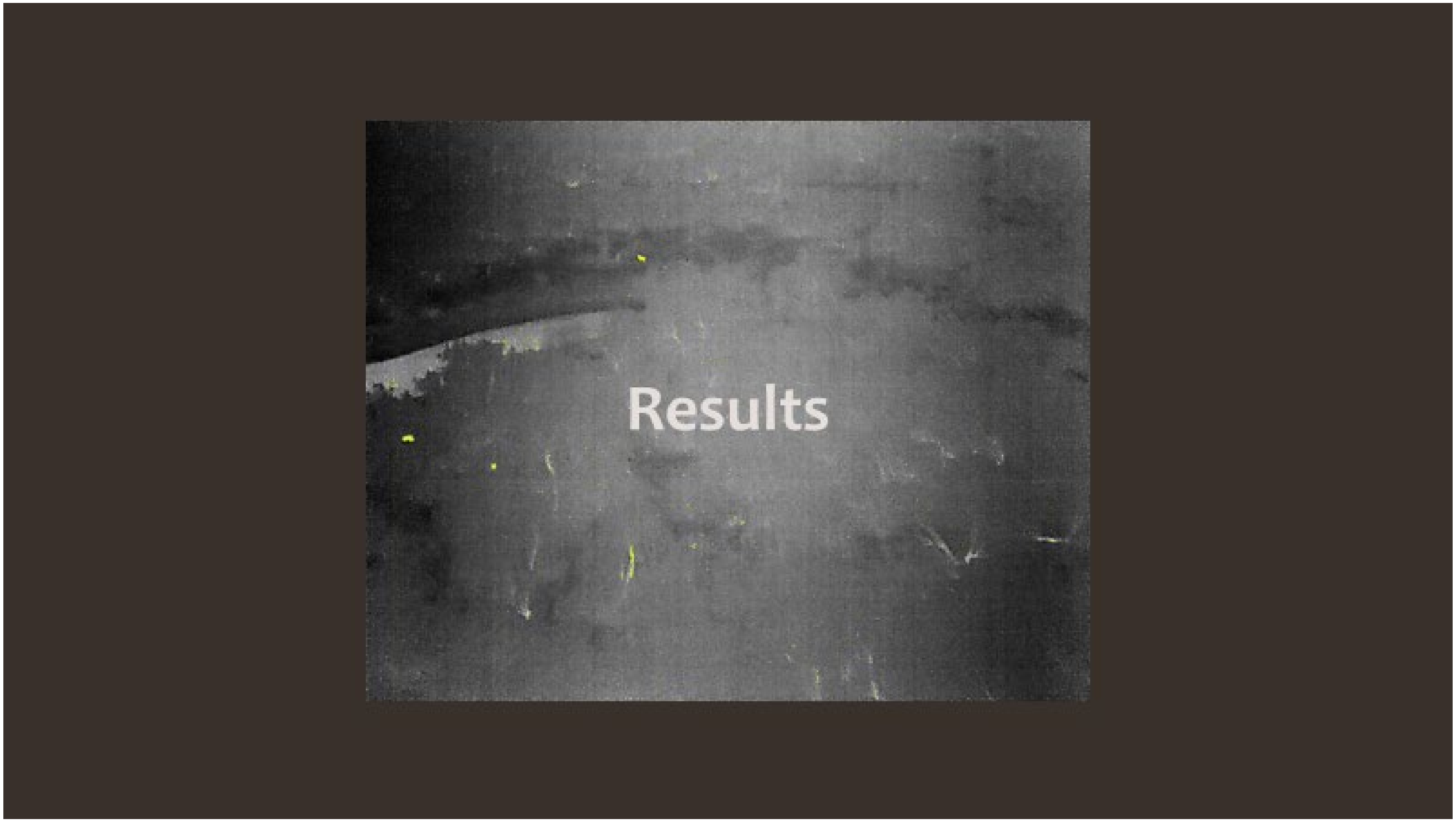
Flights

- February 19, 2022
  - 10°C
- April 30, 2022
  - 24°C
- July 23, 2022
  - 30°C
- 36 meters
- 6.7 m/s
- -20° Camera angle

Analysis

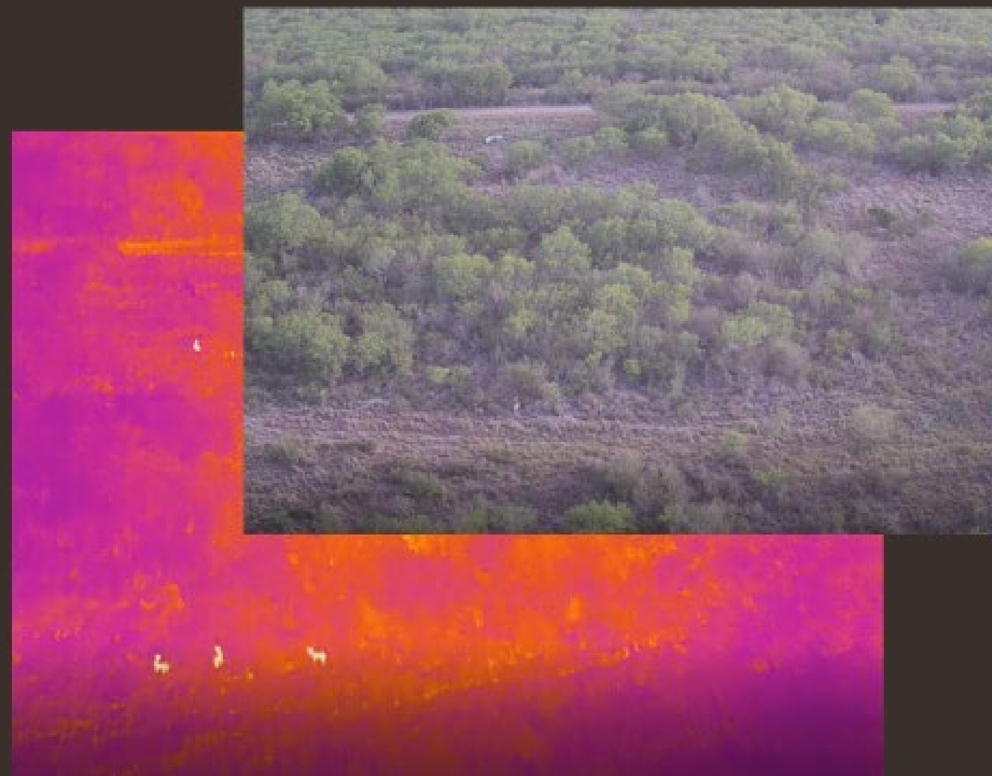
- Line Vision Ultimate
- ArcGIS Pro
  - Video Multiplexer
  - Full Motion Video
    - Mark Deer Locations
  - Measured the perpendicular distance from transect to each deer location




Results

Results Daytime

- Detection Probability:
  - ρ = 0.58-1.00
- Under 21°C



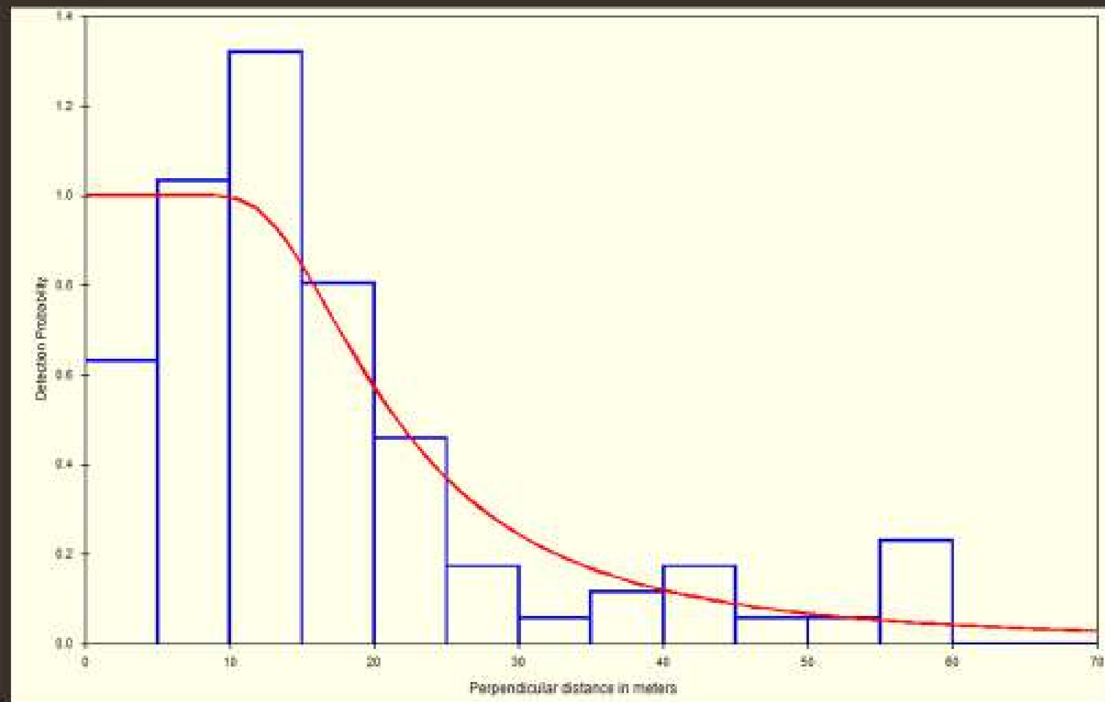
Results Nighttime

- Detection Probability:
  - p = .63-1.00
- >21 °C


Results
Isotherm vs Traditional
• No drastic differences in number of detections
• Higher contrast imagery
• >21°C
Cold
Hot
Cold
Hot

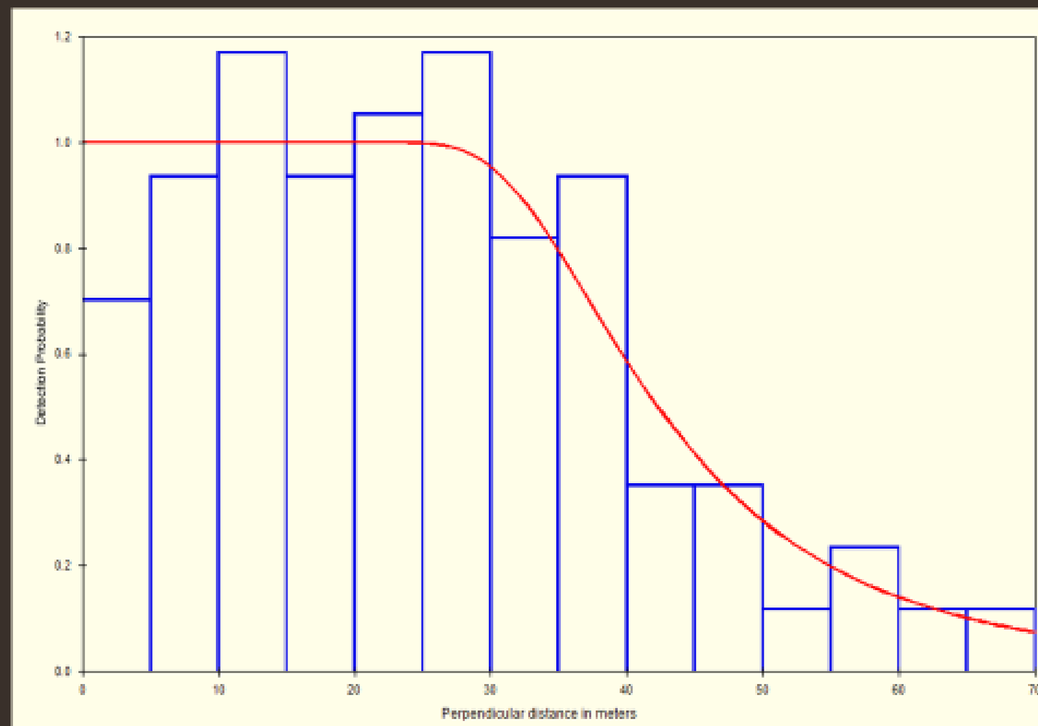
Results
February 19, 2022

- 10°C
- Thresholds
  - Lower: 10°C
  - Middle: 15°C
  - Upper: 26°C
- 89 detections



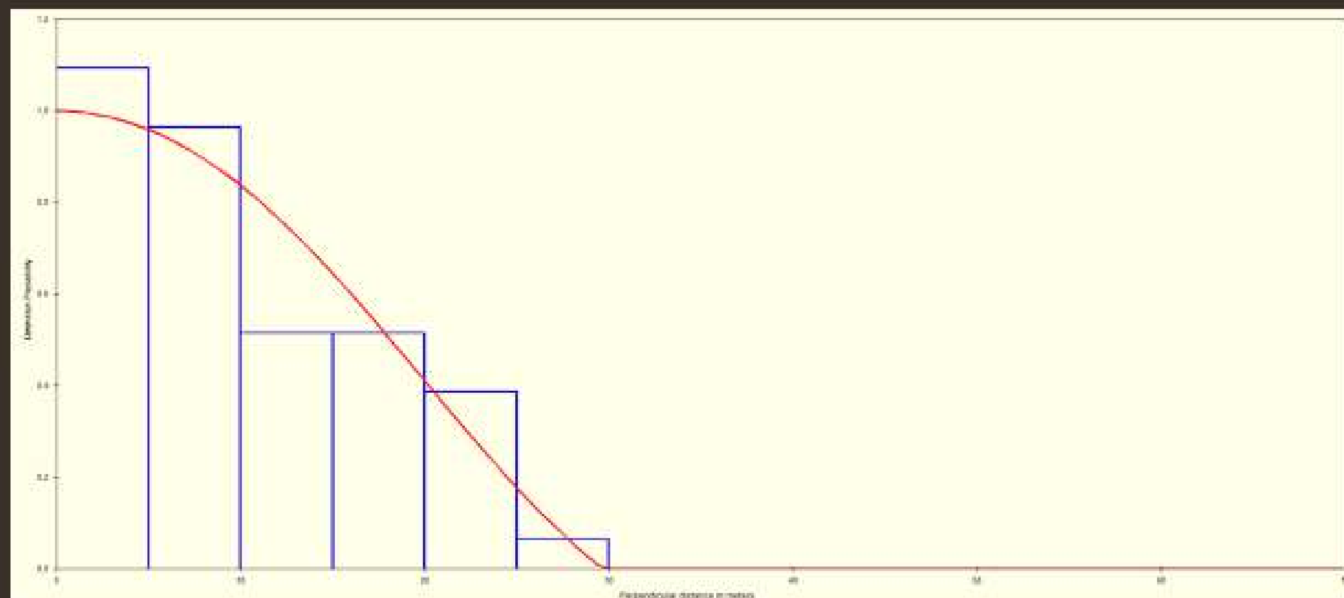
Results
April 30, 2022

- 24°C
- Thresholds
  - Lower: 24°C
  - Middle: 32°C
  - Upper: 36°C
- 60 detections



Results
July 23, 2022

- 30°C
- Thresholds
  - Lower: 30°C
  - Middle: 35°C
  - Upper: 44°C
- 55 detections



Conclusions

- Nighttime drone surveys with a thermal can be used to accurately estimate deer populations in south Texas.
- Season of surveys effects detection probability in terms of swath width most likely due to changes in canopy cover.
- Isotherm capabilities provides higher contrast imagery and can be used to survey in warmer temperatures when compared to traditional thermal capabilities.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TEXAS A&M UNIVERSITY-KINGSVILLE
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UNIVERSITY
KINGSVILLE
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WeHuntWeGive.org
Houston Livestock
Show and Rodeo
NRCS
QUAIL COALITION
DSC

Controllable Factors Affecting Accuracy of Human Identification of Birds in Images Obtained during UAS Surveys

Landon R. Jones[1], Jared A. Elmore[1], Santhana K. Boopalan[2], Emma A. Schultz[1], Kristine O. Evans[1], Sathish Samiappan[2], Bradley F. Blackwell[3], Morgan B. Pfeiffer[3], and Raymond B. Iglay[1]
[1]Department of Wildlife, Fisheries, and Aquaculture, Mississippi State University, MS; landon.jones@msstate.edu
[2]Geosystems Research Institute, Mississippi State University, MS
[3]USDA, Wildlife Services, National Wildlife Research Center, Sandusky, OH

Small uncrewed aircraft systems (sUAS or drones) are increasingly used to survey and monitor wildlife species among diverse environments. Despite the popularity and advantages of sUAS technology for surveying animal populations, few studies have examined how factors controllable by the remote pilot-in-command, such as altitude, camera angle, and time of day, can affect observer accuracy when identifying animals from sUAS images. To evaluate how these three factors influence accuracy of human identification, we conducted sUAS flights and captured visual images of decoys representing 8 avian species in known locations and configurations. Our survey efforts collected images among 4 altitudes (15, 30, 45, 60 m), 2 camera angles (45°, 90°), and 3 times of day (morning, midday, afternoon). Ten experts in wildlife identification each evaluated a set of 264 sUAS images representing all treatment combinations and controls with zero decoys. Evaluations were scored on species and count accuracy. Accuracy estimates for each photo were analyzed using a generalized linear mixed model to determine differences in accuracy among altitudes, camera angles, and time of day. Increasing flight altitude resulted in decreased accuracy in animal counts overall. Accuracy was best at midday compared to morning and afternoon hours, when shadows were present or more pronounced. The angled camera (45°) enhanced accuracy compared to 90°, but only when animals were most difficult to identify and count, such as at higher flight altitudes or during the early morning and late afternoon. Our results provide recommendations for sUAS pilots to optimize the combination of flight altitude, camera angle, and time of day to improve monitoring of wildlife communities.

Controllable factors affecting accuracy of human identification of birds in images obtained during UAS surveys

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1 MISSISSIPPI STATE UNIVERSITY DEPARTMENT OF WILDLIFE, FISHERIES AND AQUACULTURE

2 MISSISSIPPI STATE UNIVERSITY GEOSYSTEMS RESEARCH INSTITUTE

3 USDA

UAS or Drones (Unoccupied Aircraft Systems)

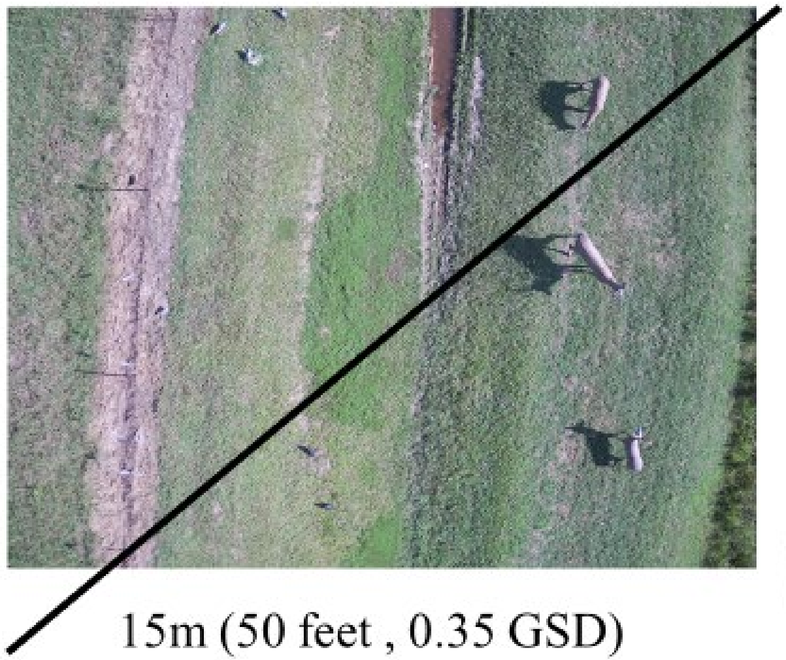
Advantages

UAS Applications

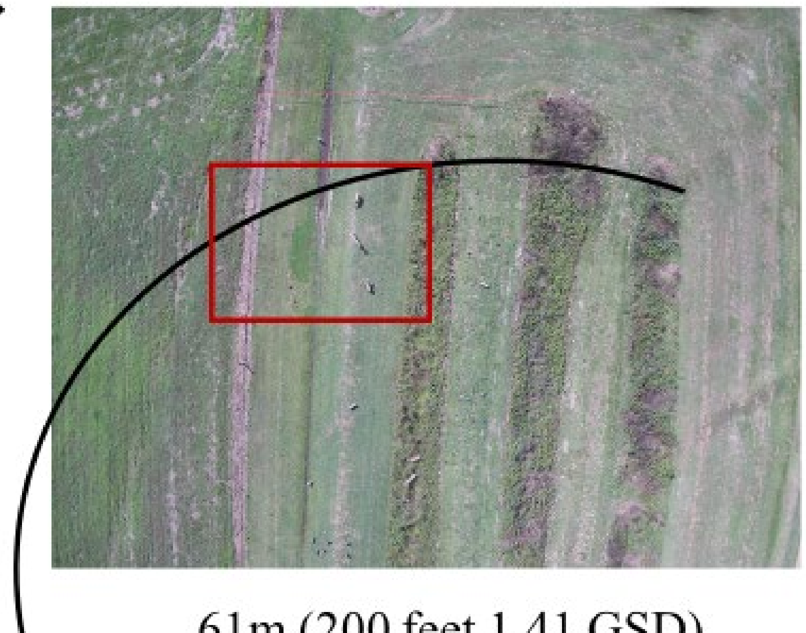
UAS Applications

Variables affecting counts

Altitude (GSD)



15m (50 feet , 0.35 GSD)



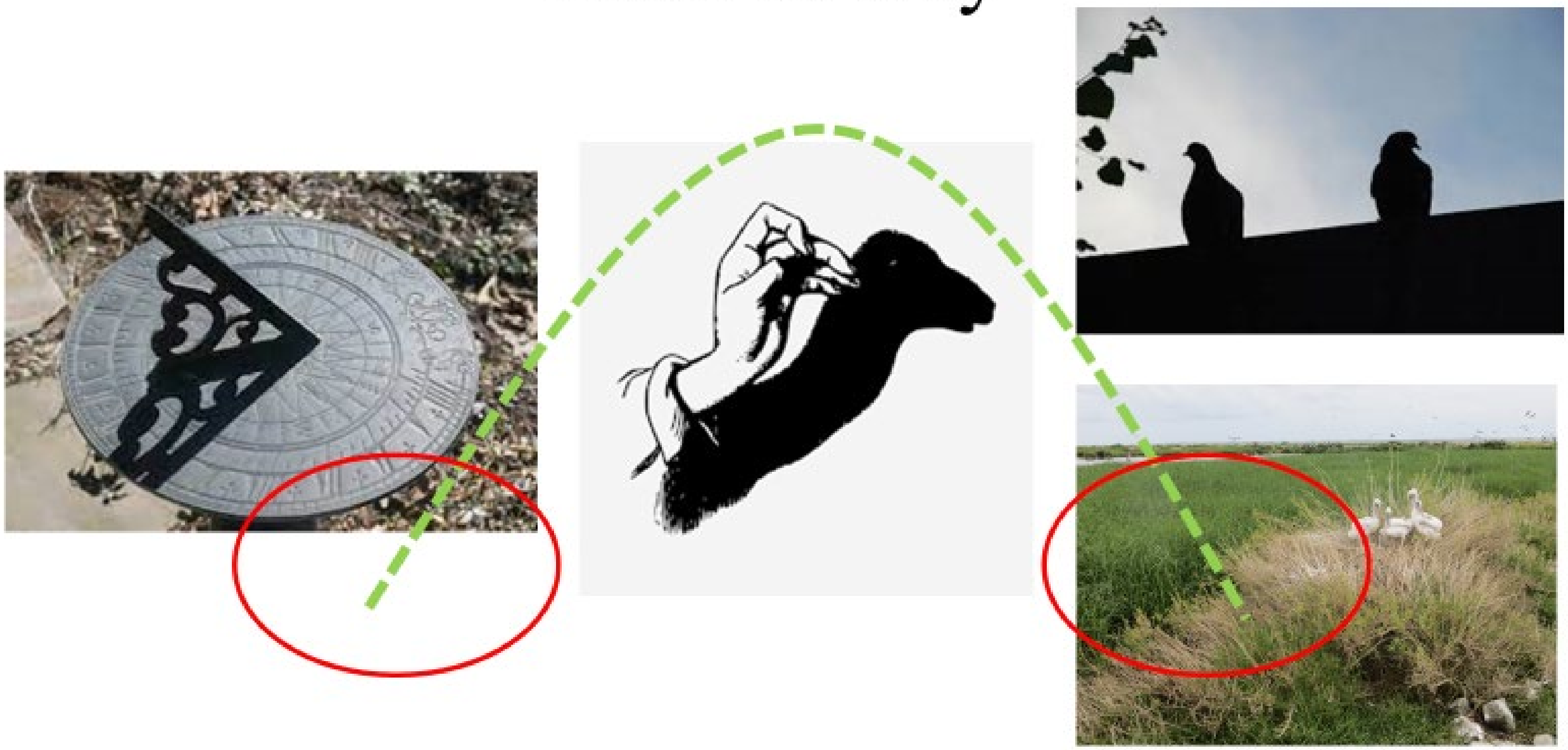
61m (200 feet 1.41 GSD)

Camera angle

45°

90°

Time of Day




Decoy Species



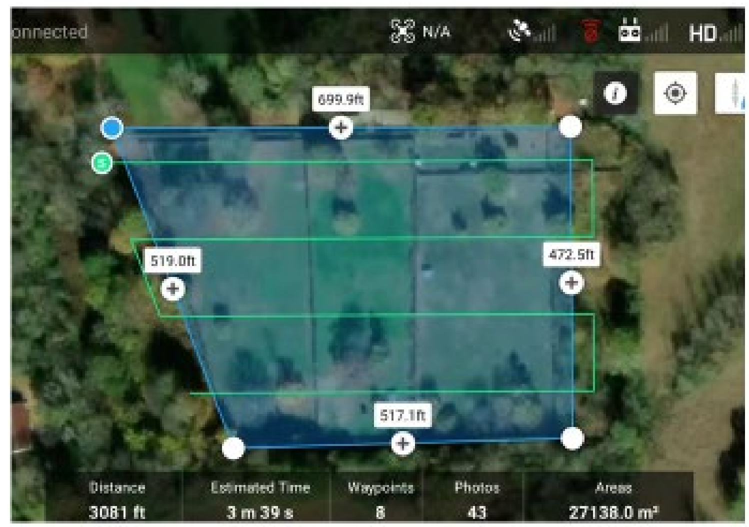




Methods: field site

Methods: UAS

DJI M200, XT2 RGB camera



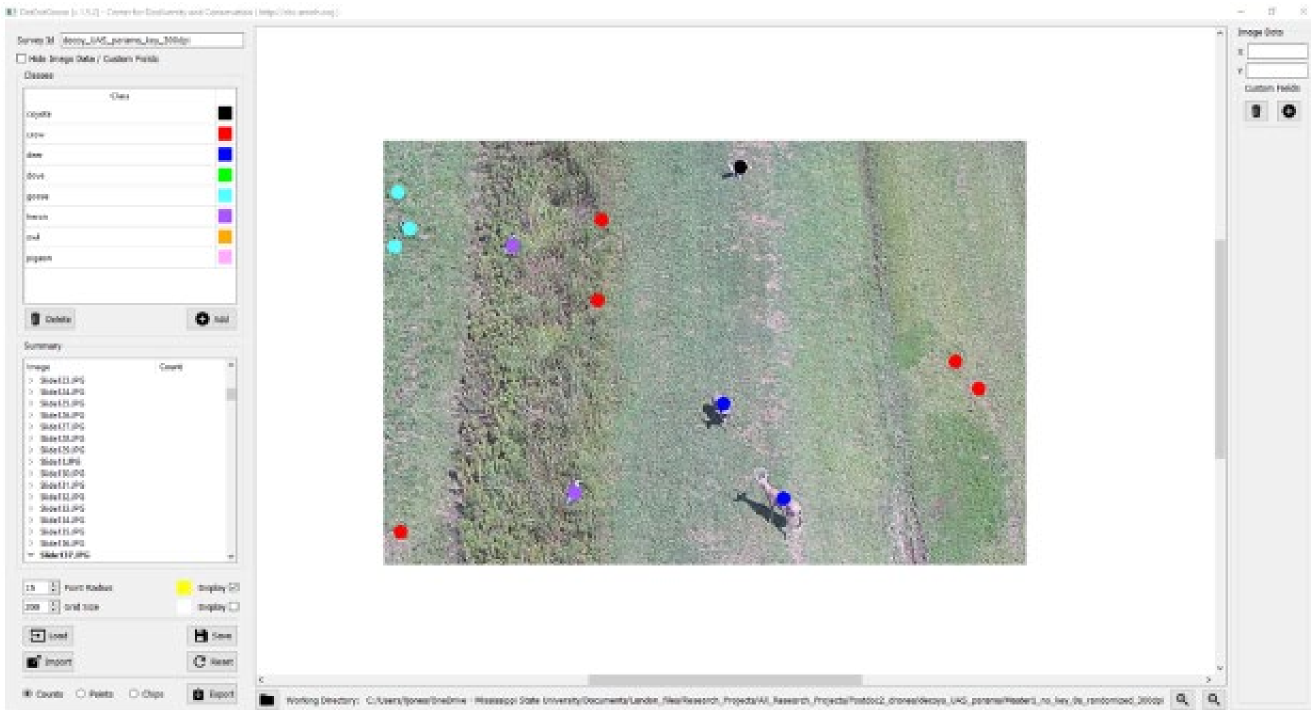
Methods: Variables

Controllable UAS factors

- 4 altitudes
  - 15m
  - 30 m
  - 46 m
  - 61 m
- 2 camera angles
  - 45°, 90°
- 3 times of day (shadows)
  - Morning
  - Midday
  - Afternoon

Methods: Human Observers

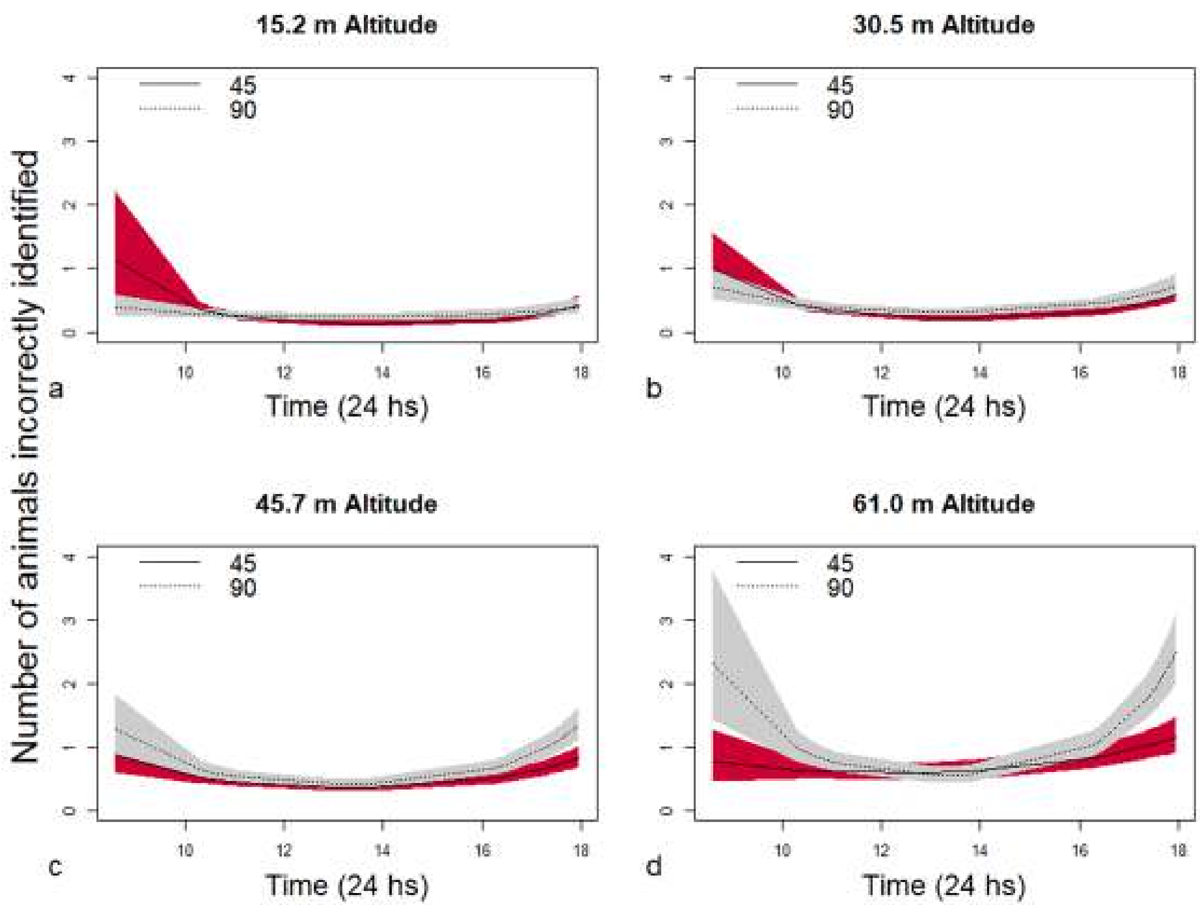
264 photos

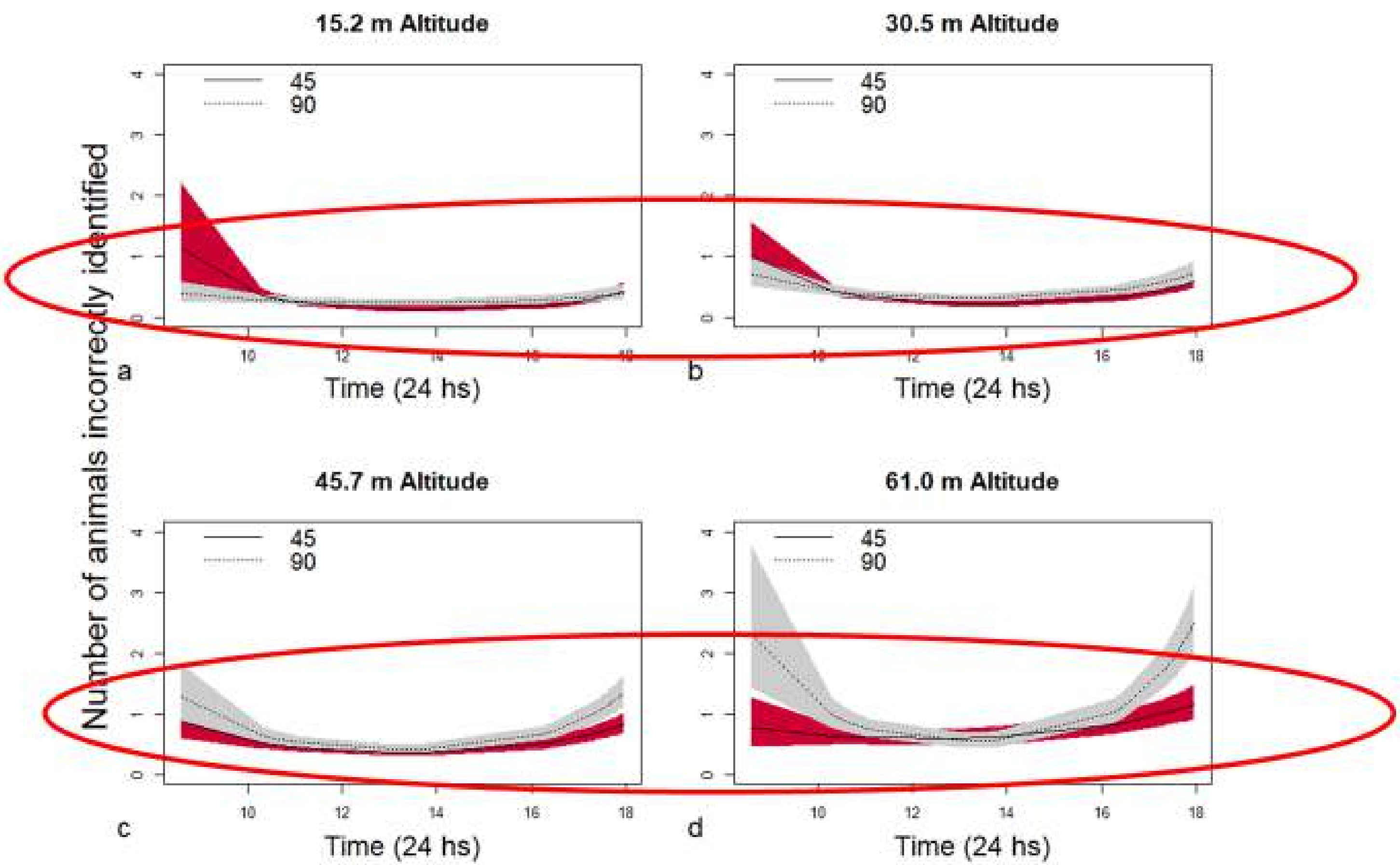


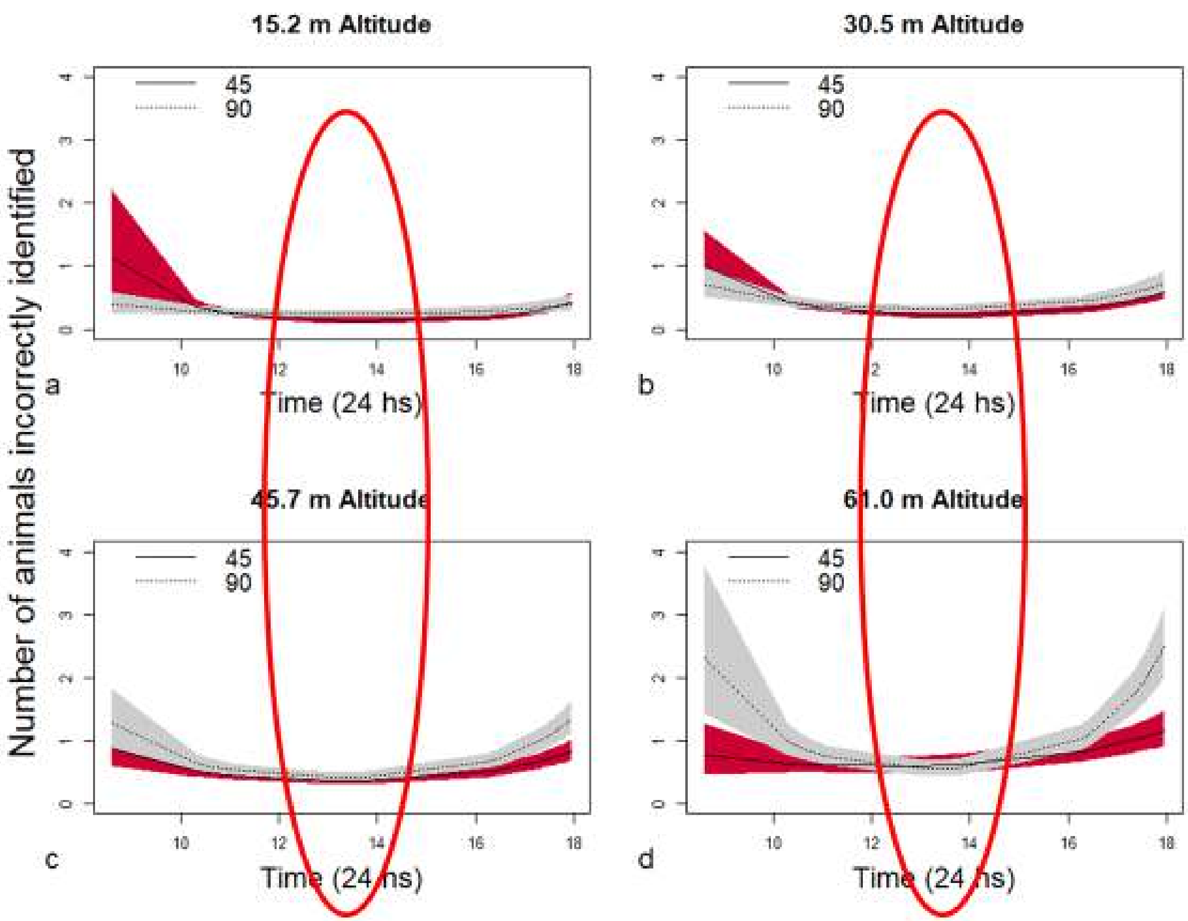
10 ‘expert’ graduate students in wildlife identification

Methods: Human Observers

- Species patterns
  - Confused
  - Missed
  - Added
- Statistics
  - Inaccuracy for each photo
  - Variables
    - Altitude
    - Camera angle
    - Time of day
  - GLMM
  - Observer as a random effect


15.2 m Altitude
30.5 m Altitude
45.7 m Altitude
61.0 m Altitude
45
90
Number of animals incorrectly identified
Time (24 hs)
a
b
c
d
0
1
2
3
4
10
12
14
16
18


15.2 m Altitude
30.5 m Altitude
45.7 m Altitude
61.0 m Altitude
45
90
Number of animals incorrectly identified
Time (24 hs)
a
b
c
d



15.2 m Altitude
30.5 m Altitude
45.7 m Altitude
61.0 m Altitude
45
90
Number of animals incorrectly identified
Time (24 hs)
a
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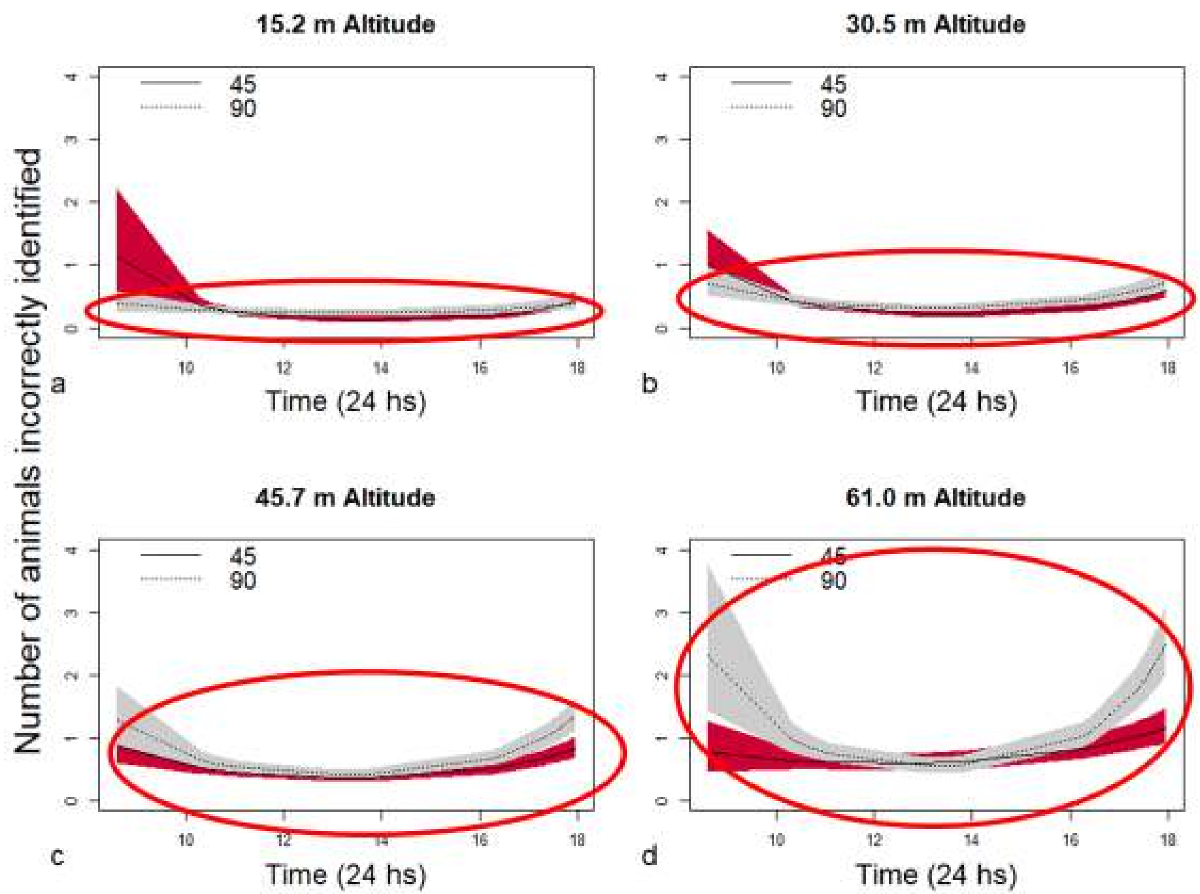
15.2 m Altitude
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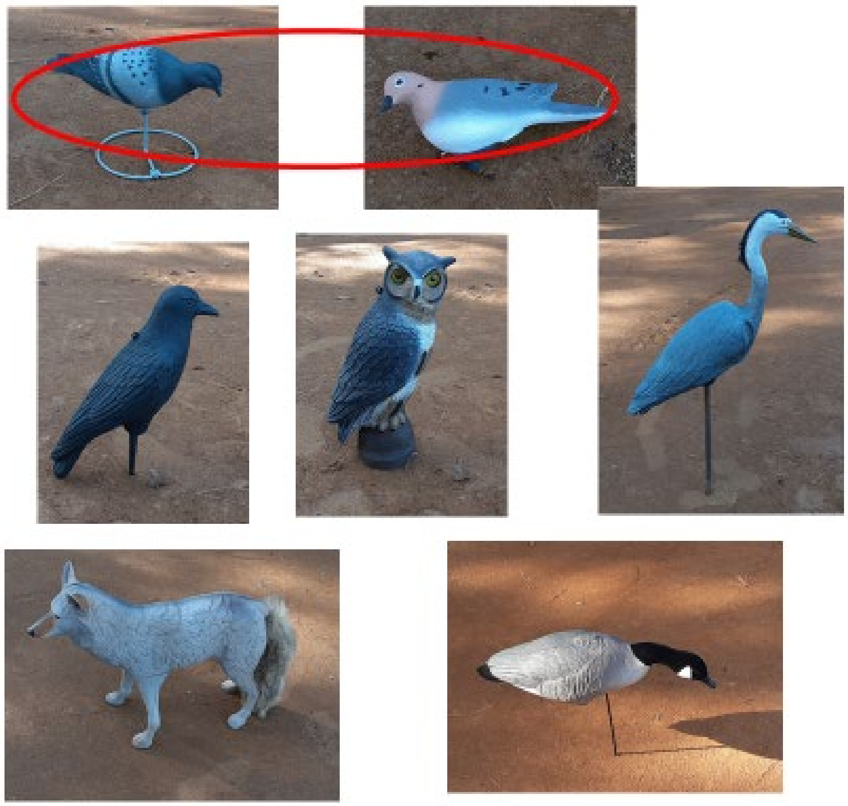
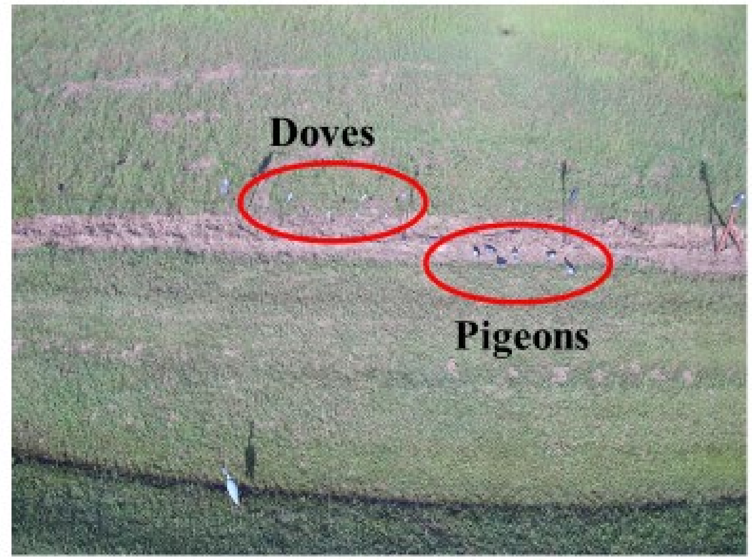
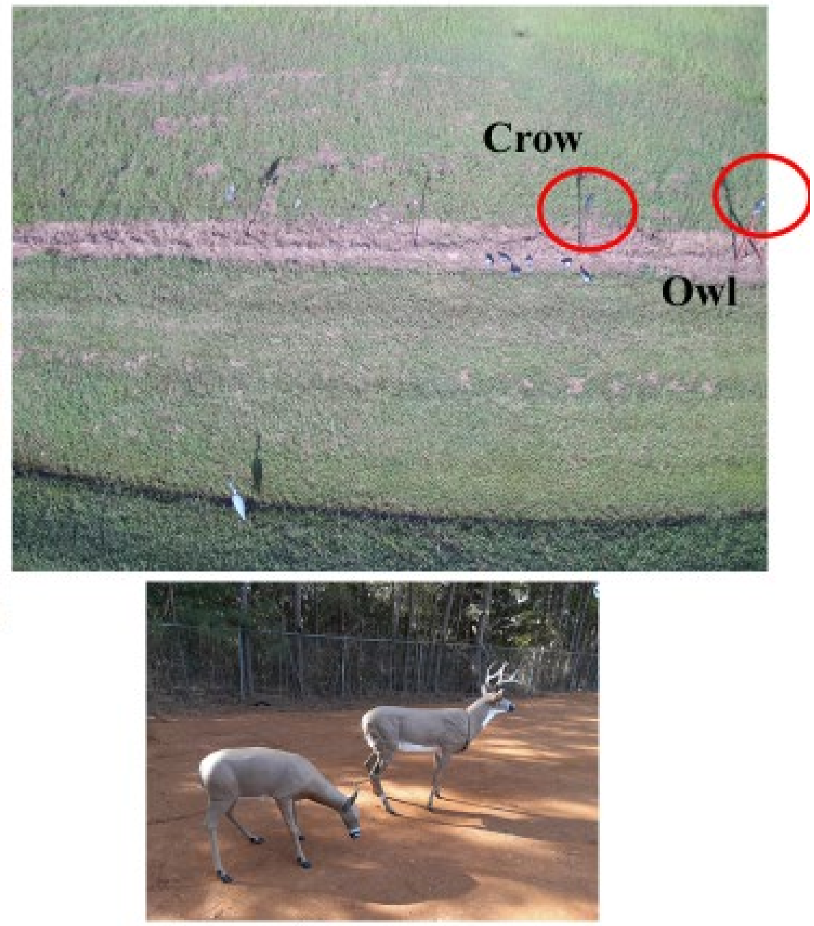
45
90
Number of animals incorrectly identified
Time (24 hs)
a
b
c
d
0
1
2
3
4
10
12
14
16
18

Results: Species Patterns

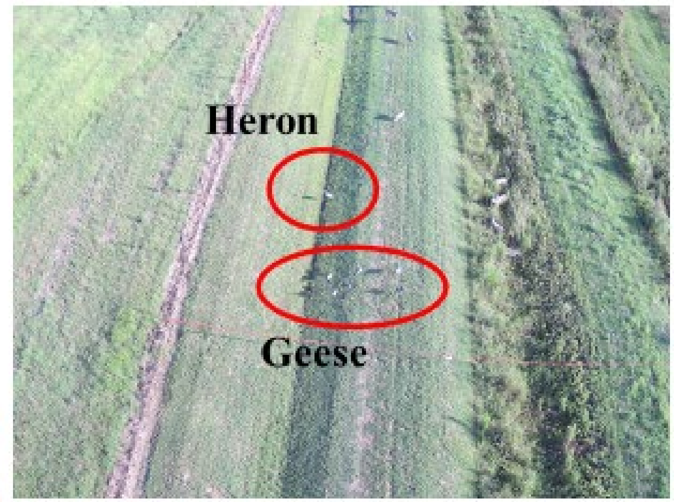




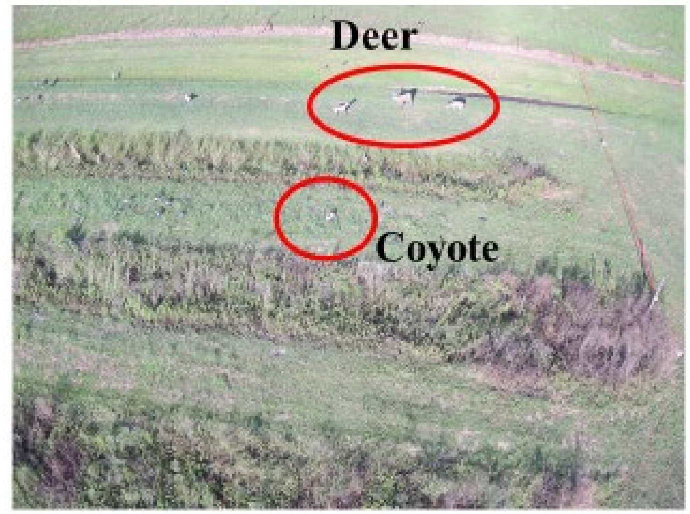
Results: Species Patterns



Results: Species Patterns



Results: Species Patterns



Recommendations

Recommendations

Recommendations

Dulava et al. 2015
≥ 0.50 GSD

Hodgson et al. 2018
≥ 2.47 GSD

This study:
0.35 – 1.41 GSD

Acknowledgements & Questions

USDA

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FEDERAL AVIATION ADMINISTRATION

Wesley Major Mike DiPilato

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AI for Detection and Classification of Wildlife from UAS Imagery

Santhana Krishnan[1], Sathishkumar Samiappan[2], Jared Elmore[1], Landon Jones[1], Morgan Pfeiffer[3], Kristine Evans[1], B. Blackwell[3], and Raymond Iglay[1]
[1]Mississippi State University; santhana@gri.msstate.edu
[2]Geosystems Research Institute, Mississippi State University
[3]USDA, Wildlife Services, National Wildlife Research Center, Sandusky, OH

Automated detection and identification of wildlife in their natural habitats from a nadir aerial view captured from small uncrewed aircraft systems (sUAS) is an important, emerging research avenue. Typical computer vision models consider wildlife in terrestrial perspective with many distinguishable features (e.g., facial features, color patterns, etc.); camera trap images for instance have both static observer and background while sUAS imagery generally has neither. Complete manual classification and localization of sUAS imagery is both unsustainable and can be erroneous (bias, human errors). In this research, we demonstrate that deep learning is promising in a real-world sUAS wildlife imagery setting: animals obscured by shadows, occupying a small ($\leq$20 x 25 pixels) object area, and having few distinguishing features due to the aerial nadir view. We discuss deep learning neural network models used in the localization, augmentation and classification of wildlife in the scene, and briefly discuss secondary applications like counting and tracking animals extending from single image classification to multiple views of one object. Experimental classification and labelling results using real, decoy, and synthetic datasets from sUAS captured imagery are provided to validate the efficiency and robustness of the proposed approach.

AI for Detection and Classification of Wildlife from UAS Imagery

Santhana Krishnan
Sathishkumar Samiappan
Jared Elmore
Landon Jones
Morgan Pfeiffer
Kristine Evans
Bradley Blackwell
Raymond Iglay

Acknowledgements:
Wesley Major (FAA)
Mike DiPilato (FAA)

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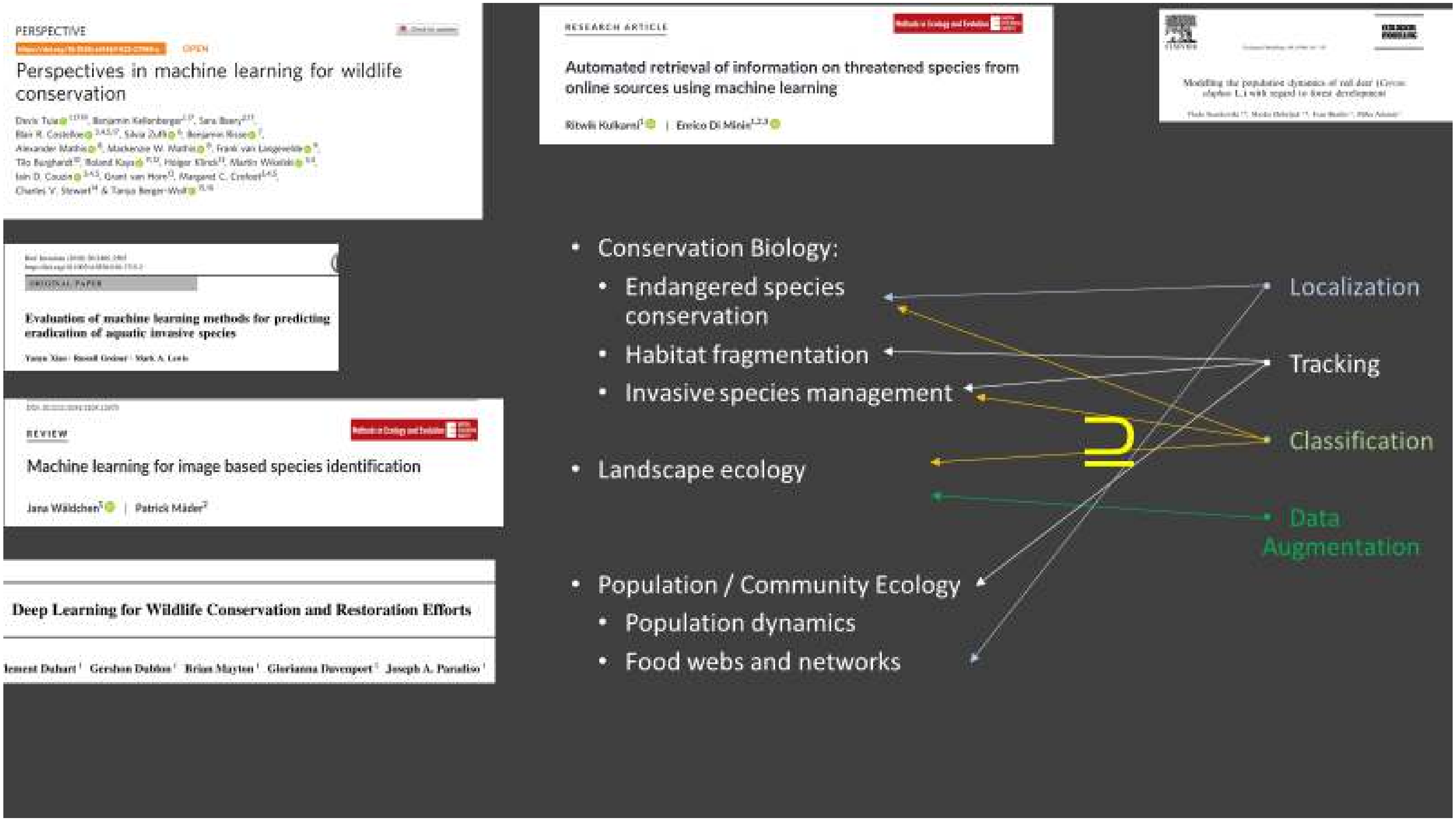
DEPARTMENT OF WILDLIFE, FISHERIES AND AQUACULTURE

USDA


PERSPECTIVE
OPEN
Perspectives in machine learning for wildlife conservation
RESEARCH ARTICLE
Automated retrieval of information on threatened species from online sources using machine learning
Ritwik Kulkarni | Enrico Di Minin
ORIGINAL PAPER
Evaluation of machine learning methods for predicting eradication of aquatic invasive species
REVIEW
Machine learning for image based species identification
Jana Wäldchen | Patrick Mäder
Deep Learning for Wildlife Conservation and Restoration Efforts
Conservation Biology:
Endangered species conservation
Habitat fragmentation
Invasive species management
Landscape ecology
Population / Community Ecology
Population dynamics
Food webs and networks
Localization
Tracking
Classification
Data Augmentation

Agenda

UAS image understanding

Applications

- Localization (Fusion)
- Classification (Fusion + shadow extension)
- Augmentation (GAN based Data Generation)
- Counting (Quail Detection with Thermal imagery)

Questions & Extensions

UAS Image Issues

Environment/ Background

Occlusions

NO Distinguishing features

Small Object Size

Small Annotated Dataset

UAS Image Issues

Environment/
Background

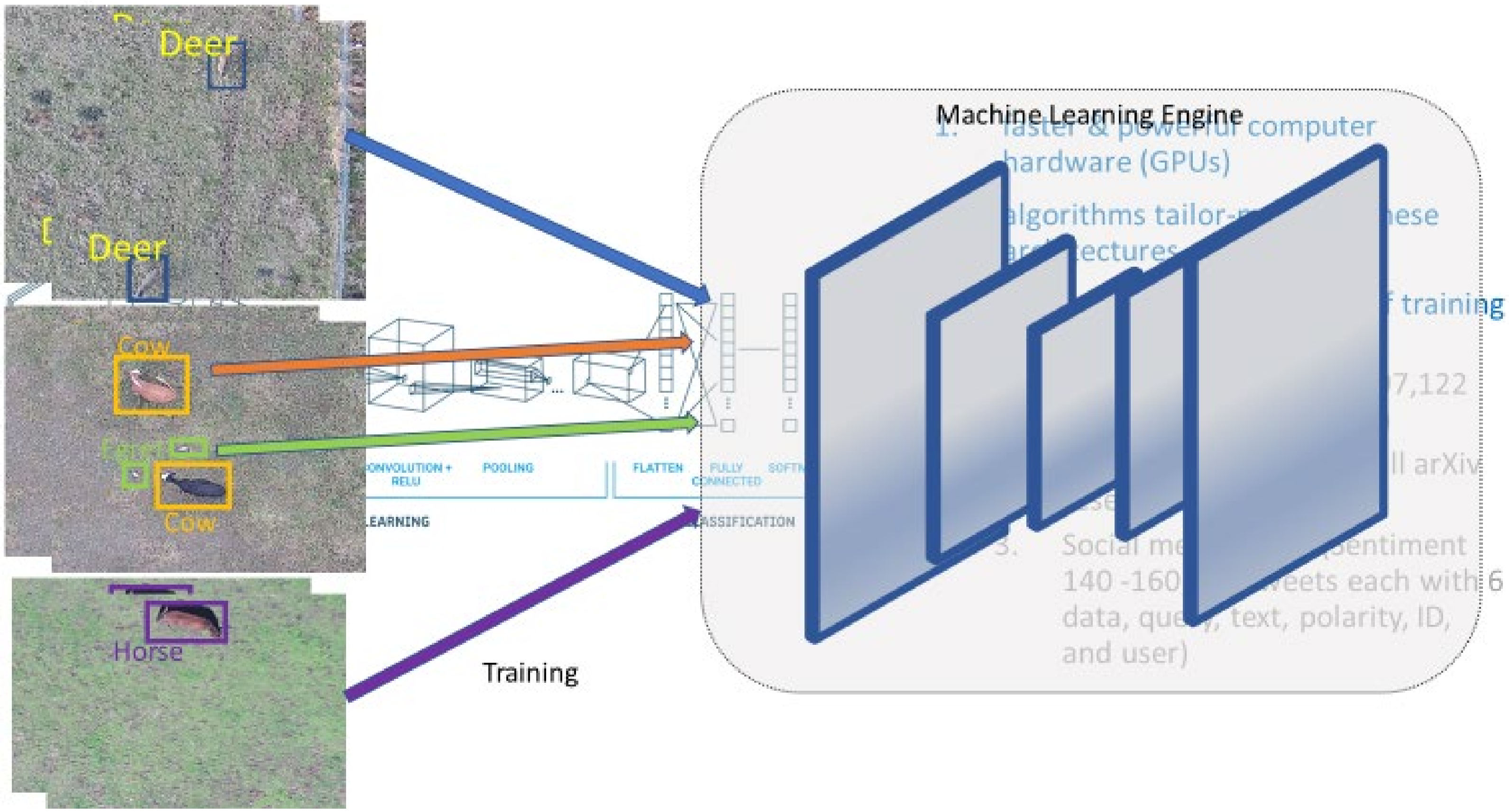
Occlusions

NO Distinguishing
features

Small Object Size

Small Annotated
Dataset

Why is ML successful in classification?



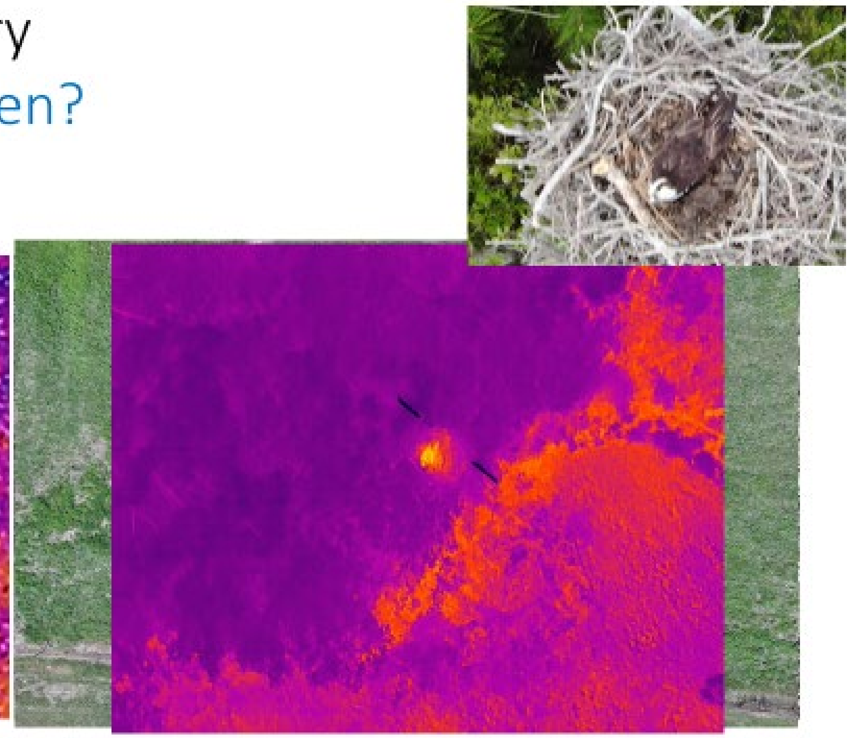
Application 1 – Localization / Classification

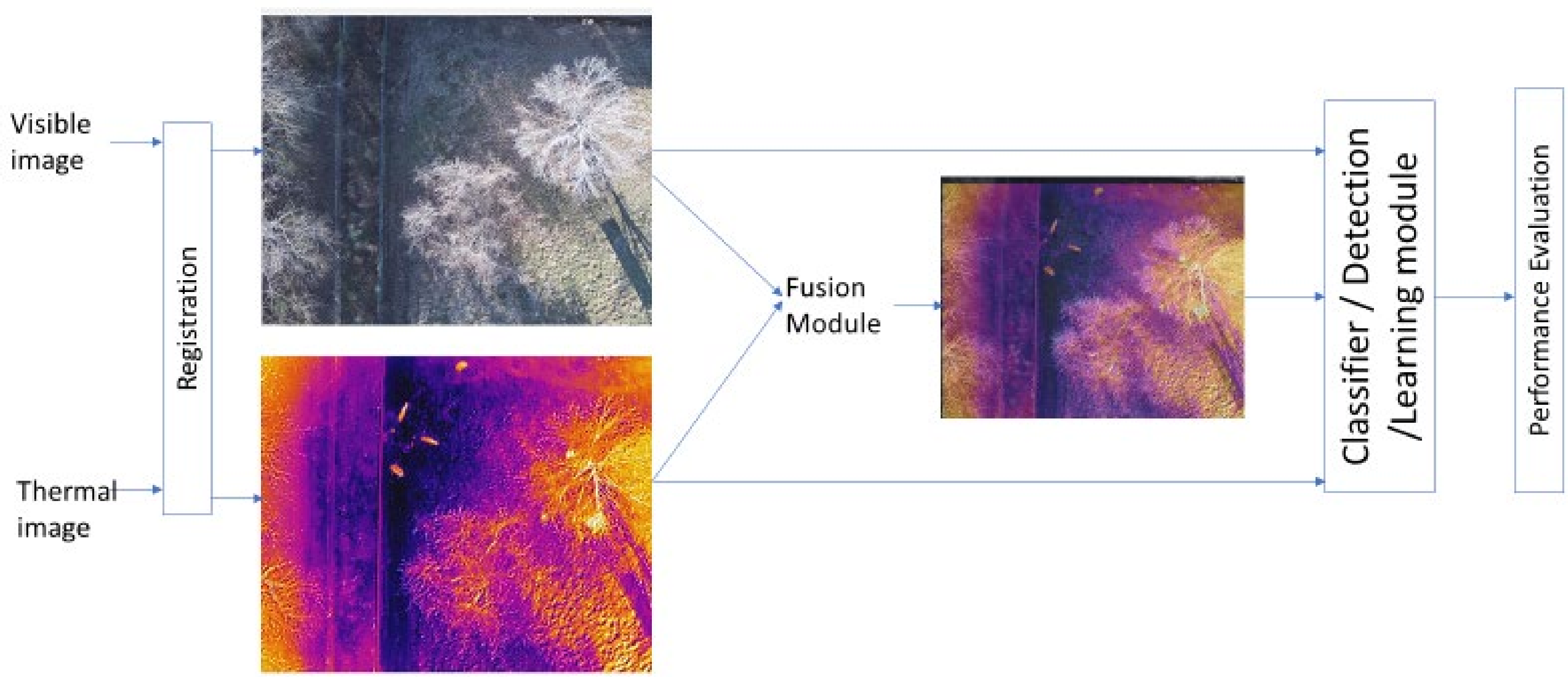
Localization ---Two Complementary Information Sources

Thermal & Visible imagery

Which to choose and when?

Deer Horse Hawk




Visible
image
Registration
Thermal
image
Fusion
Module
Classifier / Detection
/Learning module
Performance Evaluation

Fusion for Localization/ Classification

Domain adaptation:

Combine info from thermal images to visible images.

Laplacian Pyramid

Guided Filter

Thermal Only

Visible Only

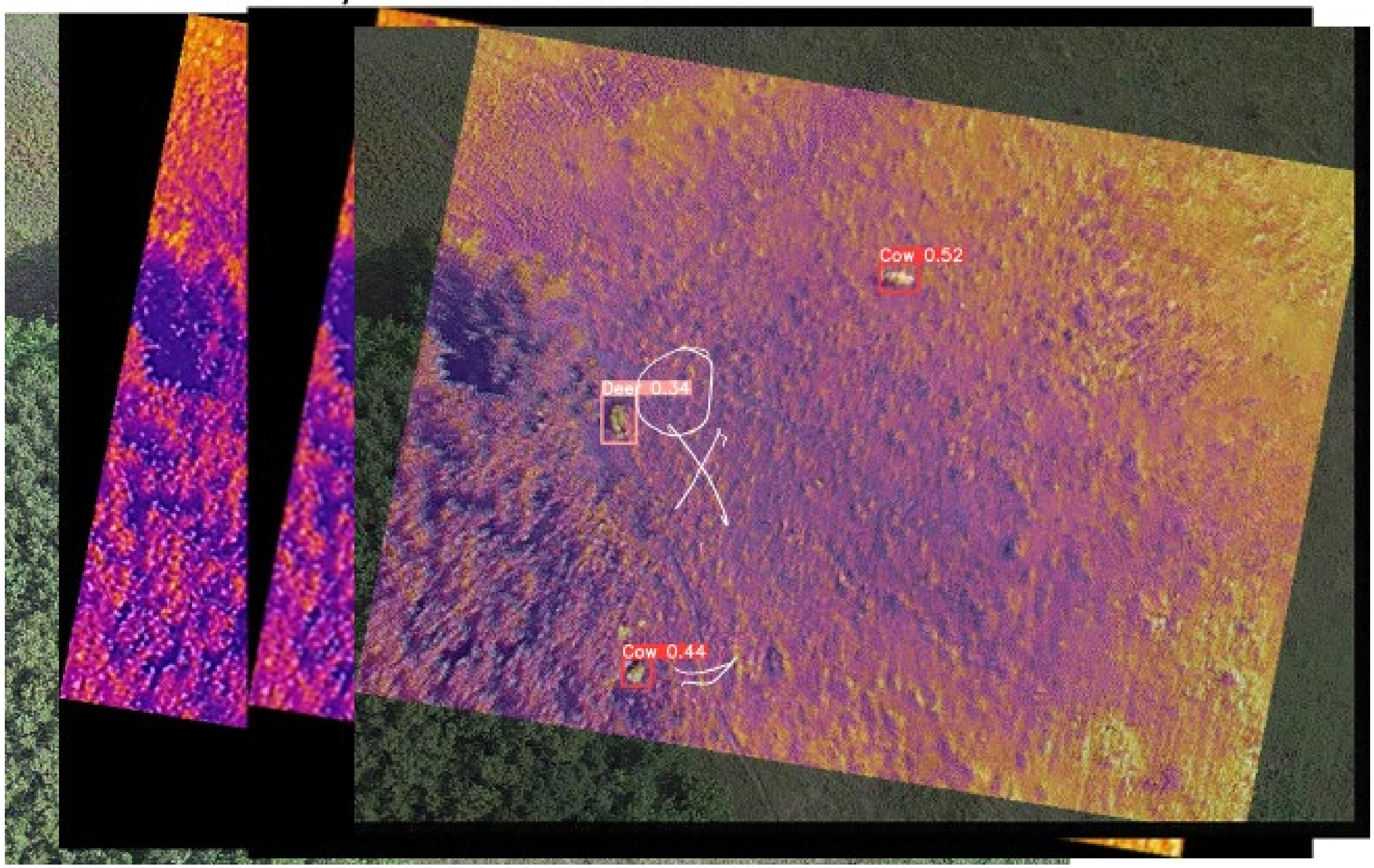
Fusion for Localization/ Classification

Laplacian Pyramid

Guided Filter

Thermal Only

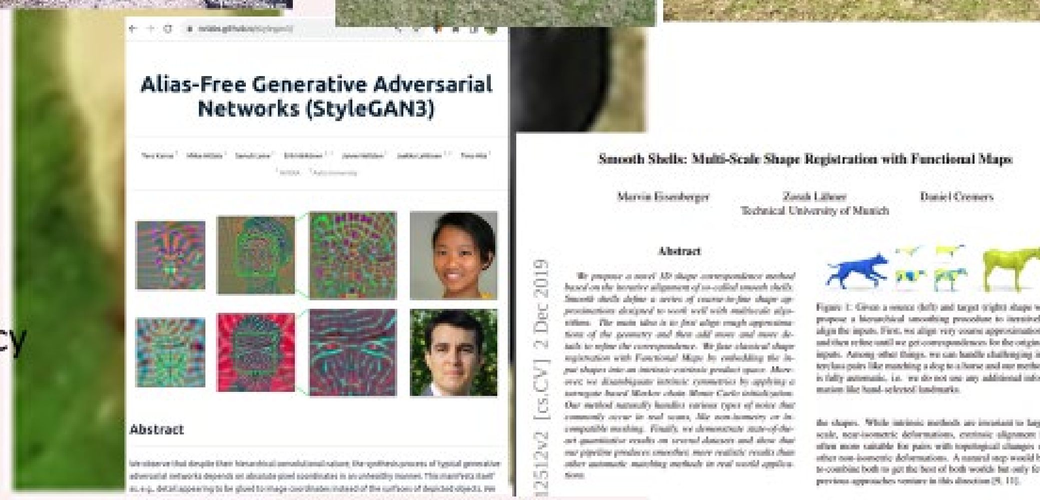
Visible Only



Application 2 – Extend Classification

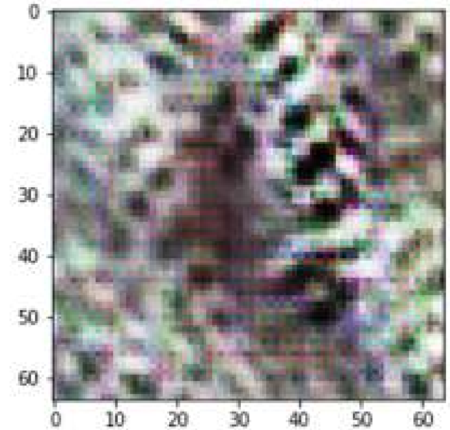
Shadow Extraction for Classification

1. Extract Shadows
2. Associate Object to Shadow
3. Lift the 2D object to a 3D with Shadow
4. Compare Classification Accuracy



Application (?) – Augment Data

Data Augmentation



Why bother?

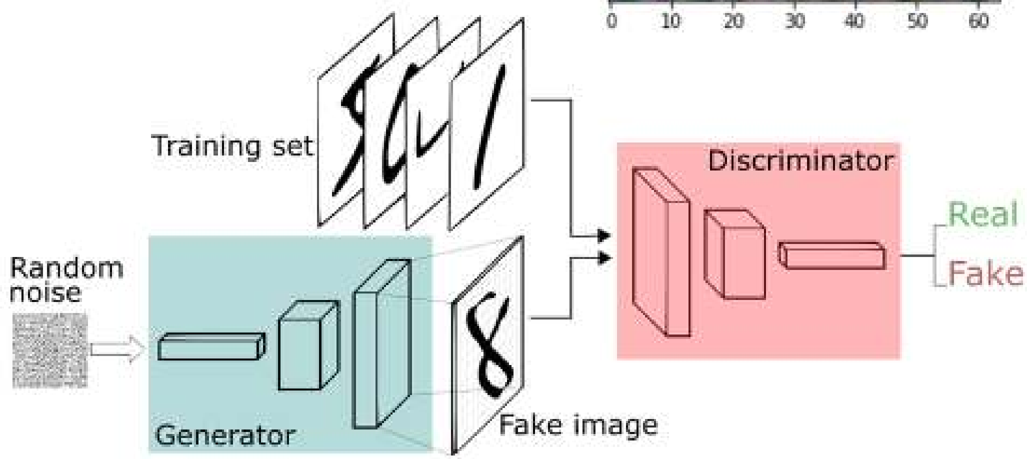
GAN

Network Structure

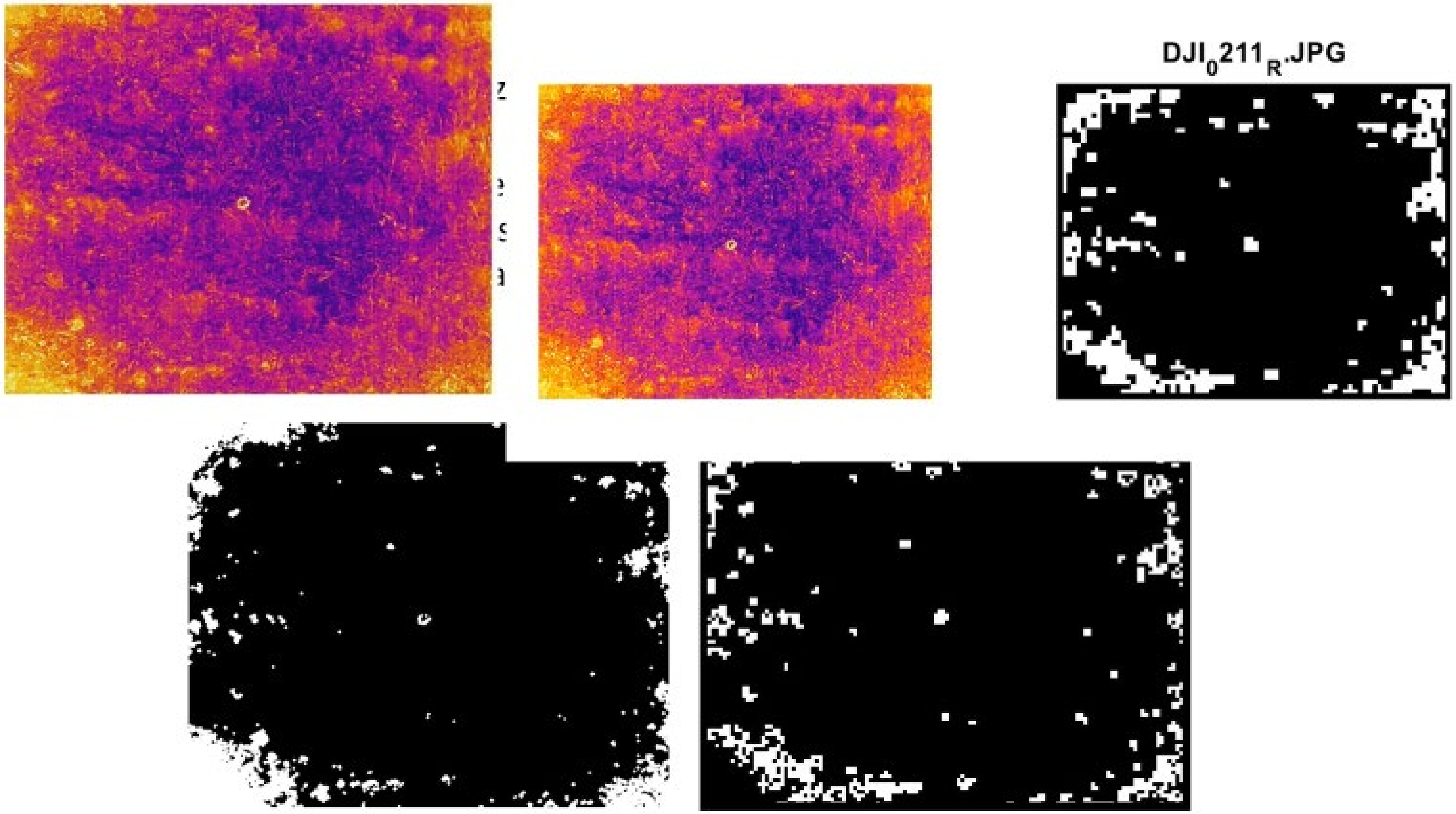
Evaluation metric

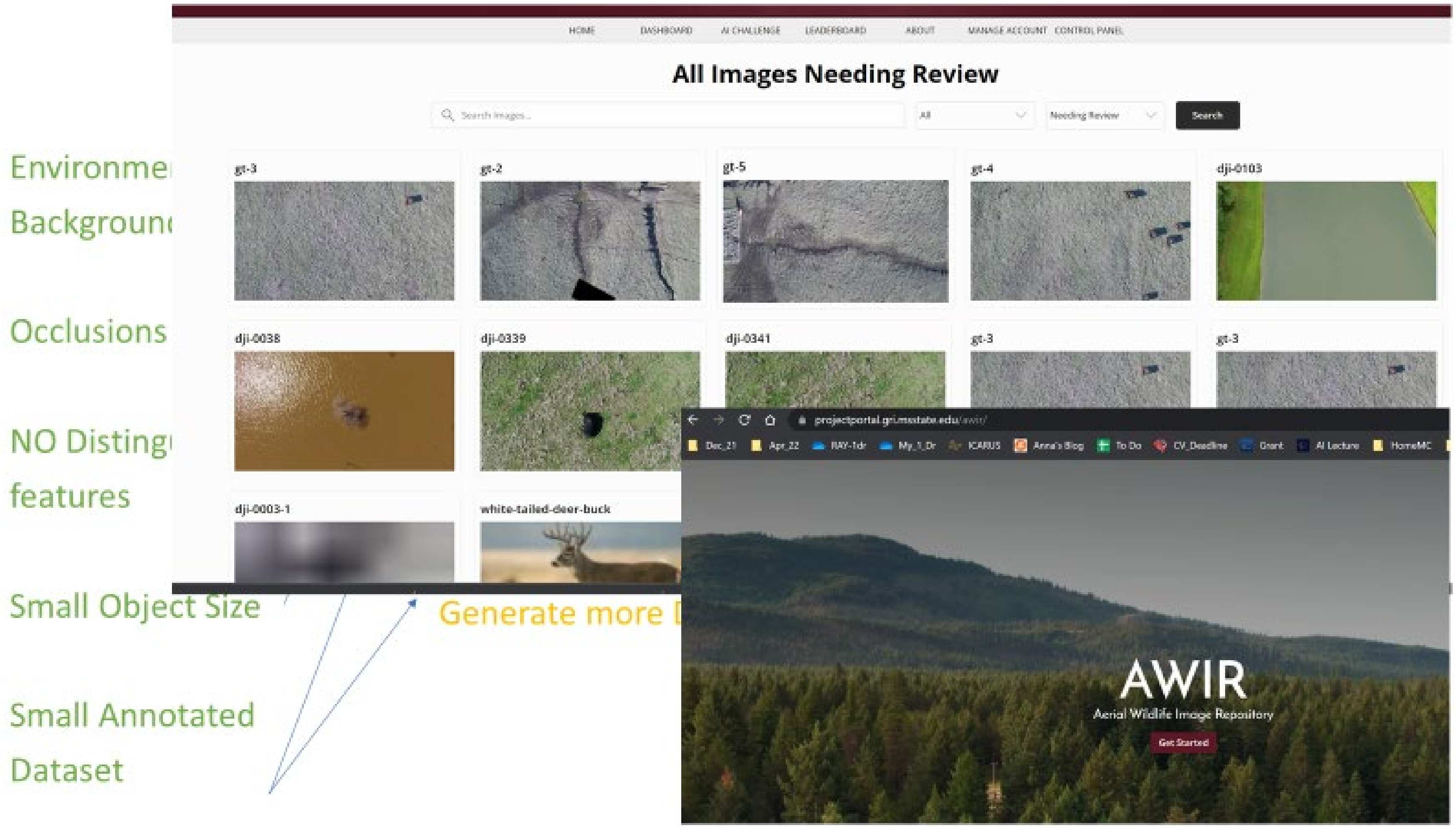
Multiple views of one object

What Next?



Application 3 – Counting


DJI$_{0}$211$_{R}$.JPG


Environme
Backgroun
Occlusions
NO Disting
features
Small Object Size
Small Annotated
Dataset
Generate more
HOME
DASHBOARD
AI CHALLENGE
LEADERBOARD
ABOUT
MANAGE ACCOUNT
CONTROL PANEL
All Images Needing Review
Search
gt-3
gt-2
gt-5
gt-4
dji-0103
dji-0038
dji-0339
dji-0341
gt-3
gt-3
dji-0003-1
white-tailed-deer-buck
projectportal.gri.msstate.edu/awir/
AWIR
Aerial Wildlife Image Repository
Get Started

- Questions?
- Thank you for your time!

A Systematic Map of Utilizing Small Unoccupied/Uncrewed Aircraft Systems (UAS) to Monitor Wildlife

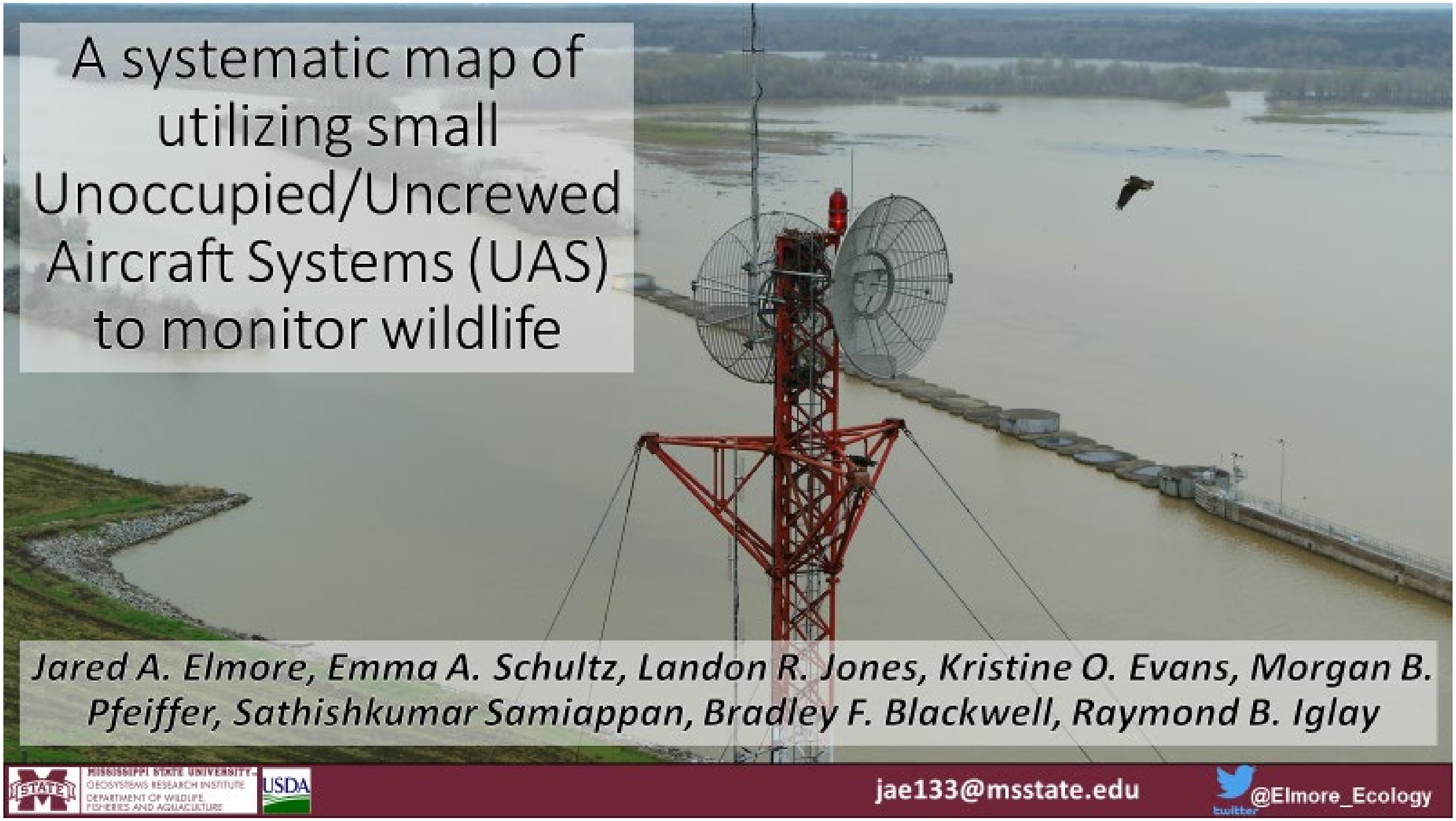
Jared A. Elmore[1], Emma A. Schultz[1], Landon R. Jones[1], Kristine O. Evans[1], Morgan B. Pfeiffer[2], Sathishkumar Samiappan[3], Bradley F. Blackwell[2], and Raymond B. Iglay[1]

[1]Mississippi State University; jae133@msstate.edu

[2]USDA, Wildlife Services, National Wildlife Research Center, Sandusky, OH

[3]Geosystems Research Institute, Mississippi State University

Small uncrewed aircraft systems (sUAS) are replacing or supplementing occupied aircraft and ground-based surveys in animal monitoring. They have the potential to improve spatial and temporal resolutions, access, safety, efficiency, and logistics, while reducing costs, observer bias, and environmental impacts. Various sUAS models and sensors are available, and usefulness depends on survey goals and design features such as target species, geographic scope, and flight conditions or considerations. However, justification for selection of sUAS models and sensors are often unreported in published literature. Moreover, most existing sUAS reviews provide limited information regarding survey goals and design considerations, performance of sUAS model and sensor technology considerations among taxonomic groups, spatial distributions of sUAS applications, or reported technology pitfalls. We developed a systematic map to collect and consolidate evidence using a comprehensive and repeatable methodology, and describe the current state of knowledge pertaining to UAS animal monitoring. We used standardized search terms to identify 4,722 individual peer-reviewed and grey literature articles, dissertations, and theses. Then, we used a tiered approach to exclude articles that did not monitor (i.e., identify, count, estimate) animals resulting in 591 articles reviewed at full text. For 216 included articles, we recorded and queried data pertaining to sUAS, sensors, animals, and methodology to produce tables, figures, and geographic maps. Our systematic map provides a useful synthesis of current sUAS applications for studying animals and identifies knowledge clusters, gaps, and trends that may influence future research directions and applications.


A systematic map of utilizing small Unoccupied/Uncrewed Aircraft Systems (UAS) to monitor wildlife
Jared A. Elmore, Emma A. Schultz, Landon R. Jones, Kristine O. Evans, Morgan B. Pfeiffer, Sathishkumar Samiappan, Bradley F. Blackwell, Raymond B. Iglay
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DEPARTMENT OF WILDLIFE, FISHERIES AND AQUACULTURE
USDA
jae133@msstate.edu
@Elmore_Ecology

Acknowledgements

- Dr. Wesley Major and Mr. Mike DiPilato
- Dr. Michael Curran & Mr. Meilun Zhou

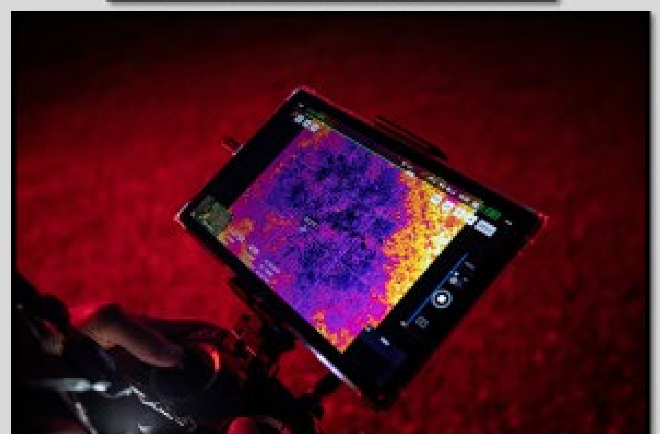

Photo: The Confluence Group

Systematic maps

- Broad questions
- Collating, cataloging, and describing evidence

Systematic Map Protocol | Open Access | Published: 30 June 2021

Evidence on the effectiveness of small unmanned aircraft systems (sUAS) as a survey tool for North American terrestrial, vertebrate animals: a systematic map protocol

Jared A. Elmore, Michael F. Curran, Kristine O. Evans, Sathishkumar Samiappan, Meilun Zhou, Morgan B. Pfeiffer, Bradley F. Blackwell & Raymond B. Iglay

Environmental Evidence **10**, Article number: 15 (2021) | Cite this article

Objective and question

- Consolidate evidence of UAS to monitor animals in terrestrial environments
- What evidence exists on the effectiveness of UAS as a survey tool for terrestrial, vertebrate animals?

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Elmore et al. 2021

Google Scholar

ProQuest Dissertations & Theses Global

Clarivate Web of Science

Scopus

EBSCO Wildlife & Ecology Studies Worldwide

Methods

- Literature search
- Article classification
- Data coding
- Mapping and presentation

Metadata specifics

StudyID	Years of study	Drone manufacturer
Authors	Country of study	Drone model
Title	State/province of study	Control type
Year of publication	Location latitude	Gimbal
Month of publication	Location longitude	Mission planning software
Day of publication	Multiple locations	Above Ground Level (AGL)
Publication type	Multiple methodologies	Flight Speed
Publication venue/journal	Land cover type	Flight pattern
Issue number	Subject family EN	Flight duration
Volume number	Subject species EN	Flight time of day
Pages	Subject species Latin	Ground control points
Peer-reviewed	Animal groups	Ground truth
URL with DOI	Purpose of the study	Sensor manufacturer
Assigned reviewer	Bias estimated	Sensor model
Language	Bias estimation methods	Field calibration
Bias consideration and factors	Comparison to other methods	Calibration type
Is raw data available	Description of other method used	Ground sample distance
Constraints	Statistical analysis	Image analysis
	Type of statistical analysis	Image preprocessing

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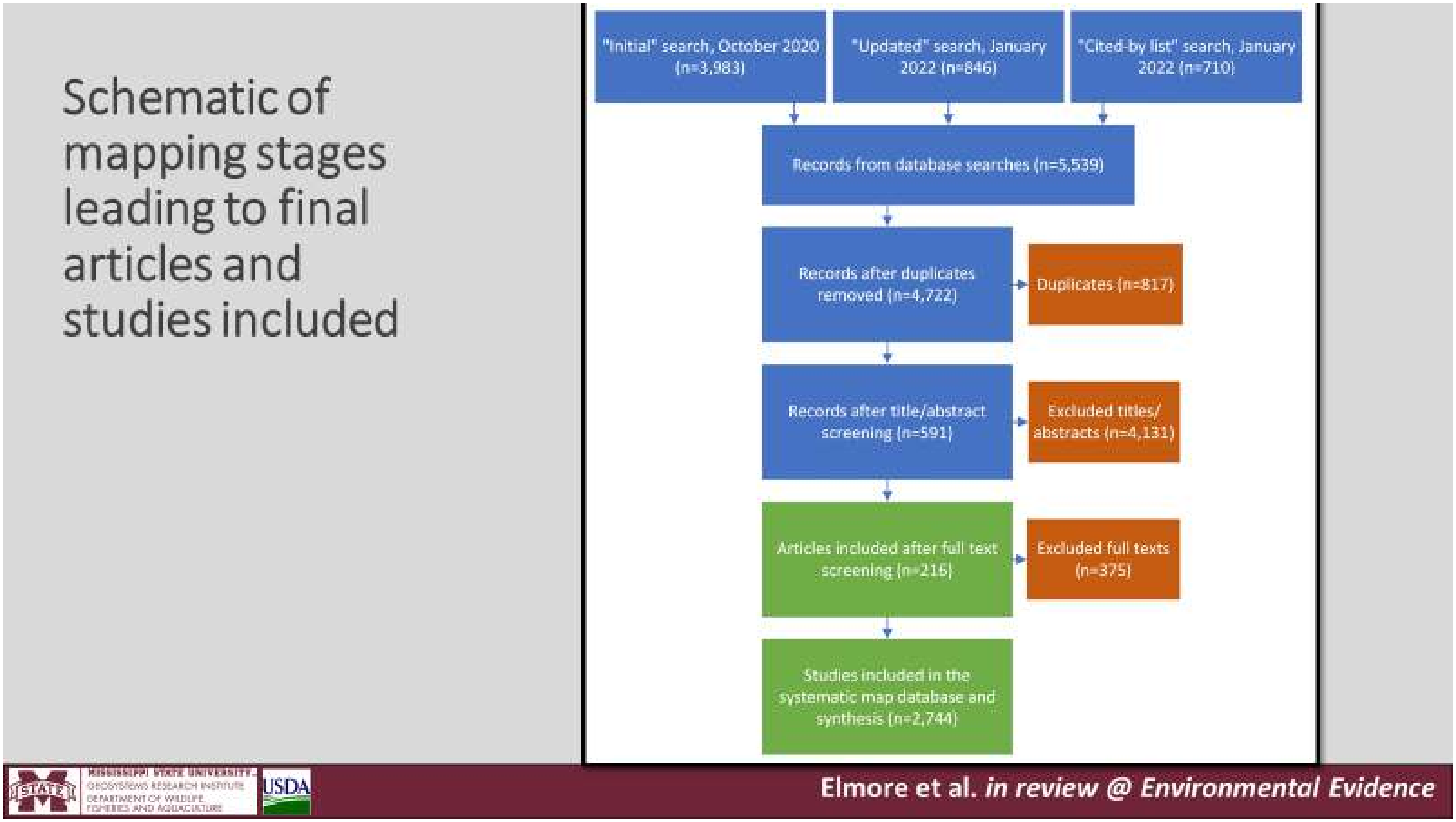
Schematic of mapping stages leading to final articles and studies included
"Initial" search, October 2020 (n=3,983)
"Updated" search, January 2022 (n=846)
"Cited-by list" search, January 2022 (n=710)
Records from database searches (n=5,539)
Records after duplicates removed (n=4,722)
Duplicates (n=817)
Records after title/abstract screening (n=591)
Excluded titles/ abstracts (n=4,131)
Articles included after full text screening (n=216)
Excluded full texts (n=375)
Studies included in the systematic map database and synthesis (n=2,744)
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USDA
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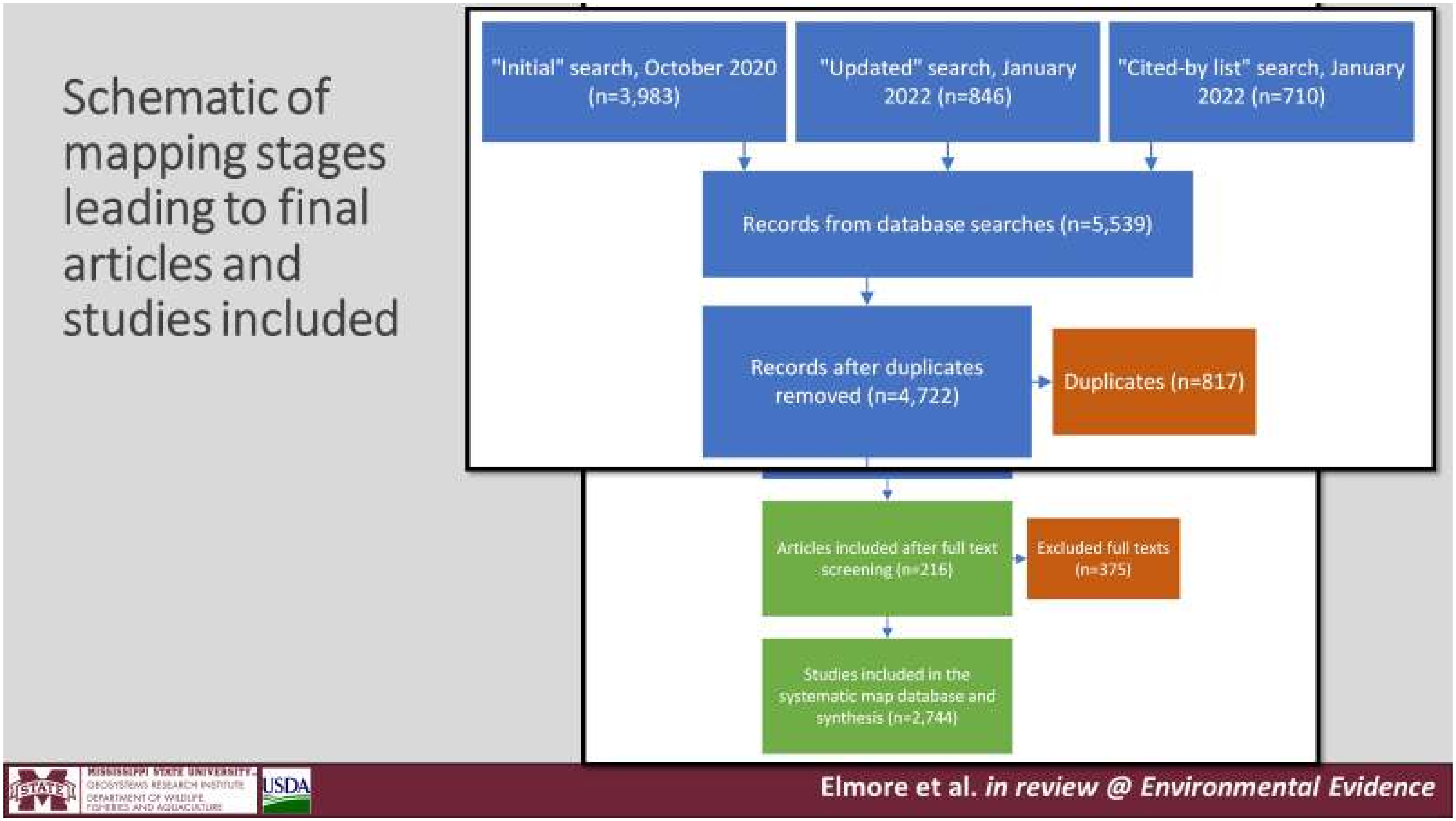
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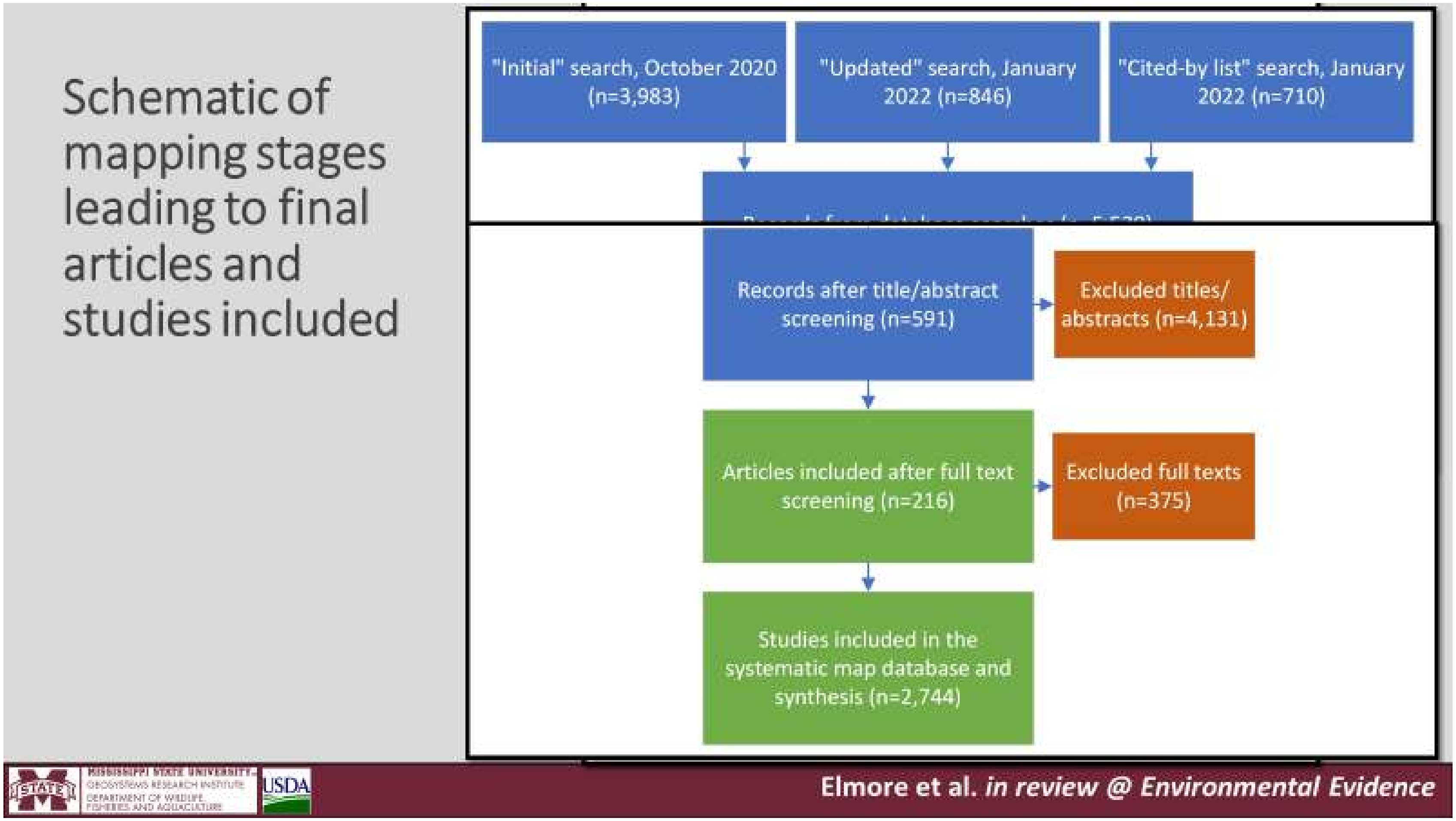
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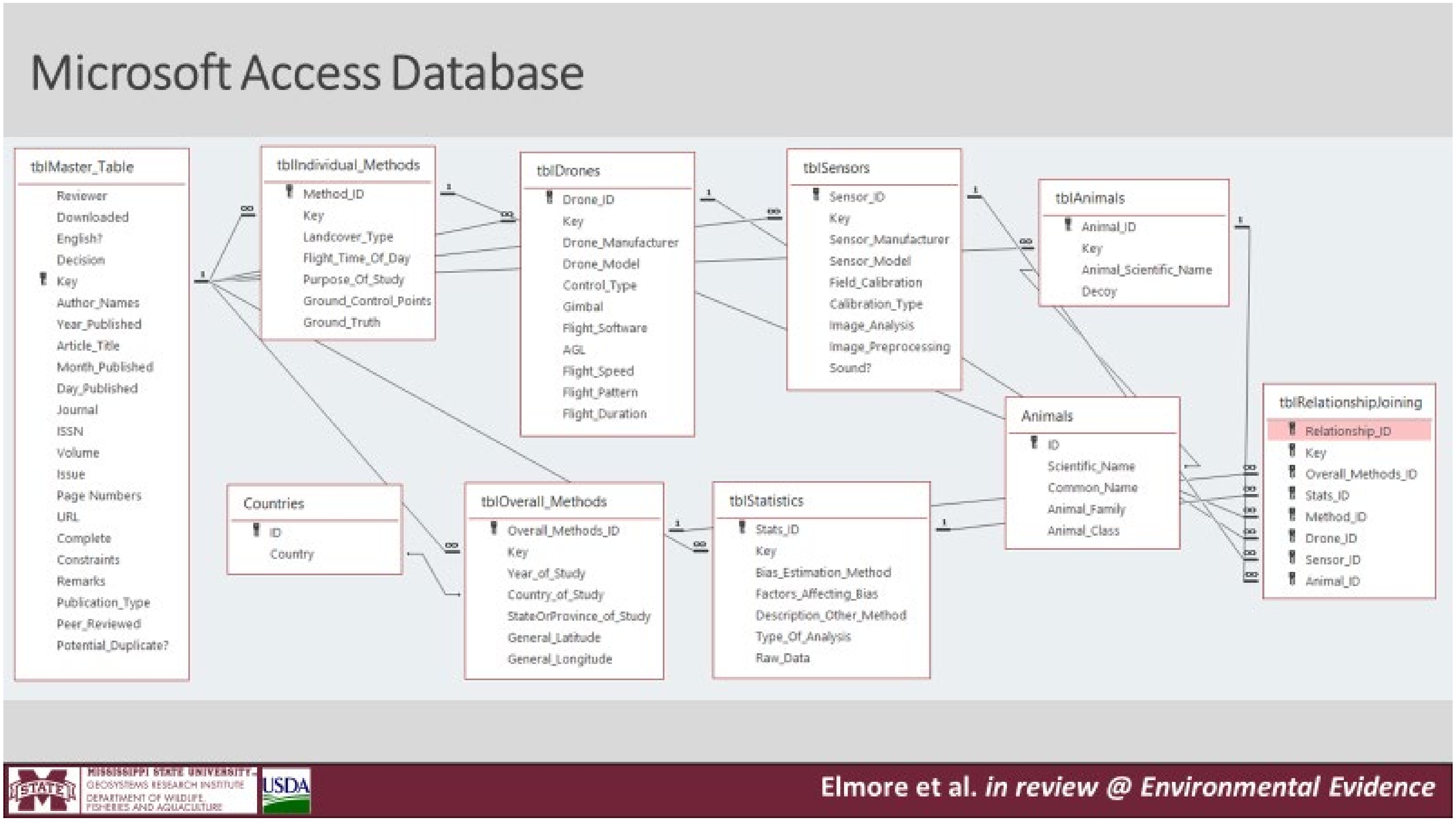
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Article_Title
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Flight_Time_Of_Day
Purpose_Of_Study
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Ground_Truth
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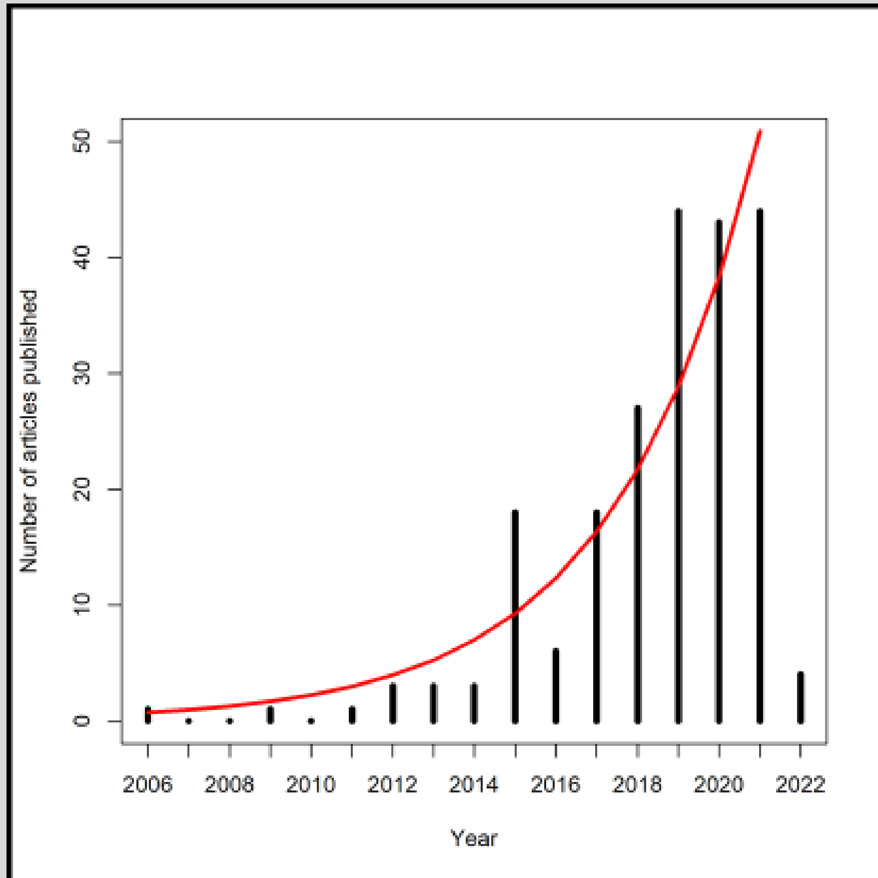
Exponential growth in number of published articles on monitoring wildlife with UAS



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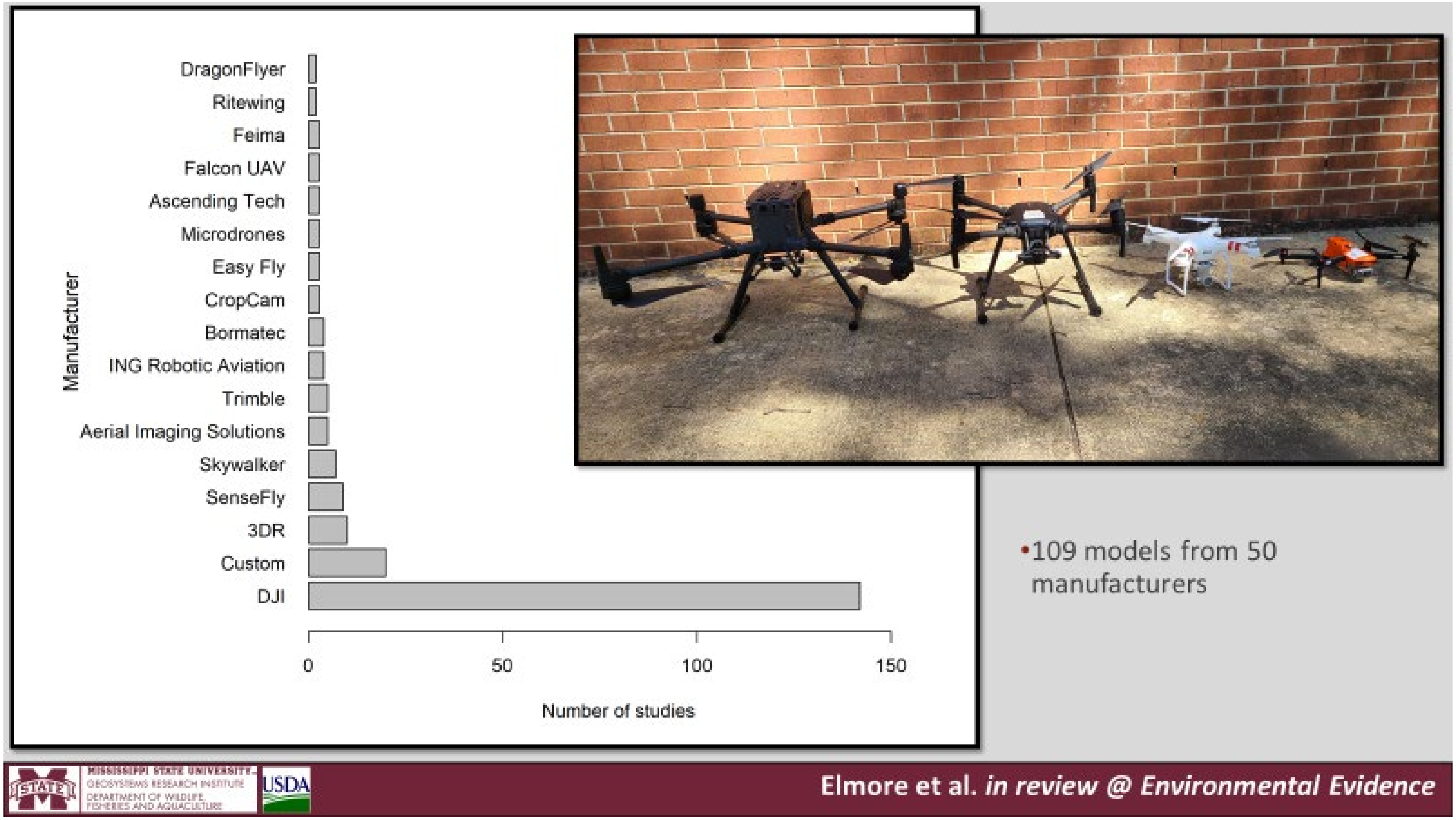
DragonFlyer
Ritewing
Feima
Falcon UAV
Ascending Tech
Microdrones
Easy Fly
CropCam
Bormatec
ING Robotic Aviation
Trimble
Aerial Imaging Solutions
Skywalker
SenseFly
3DR
Custom
DJI
Manufacturer
0
50
100
150
Number of studies
•109 models from 50 manufacturers
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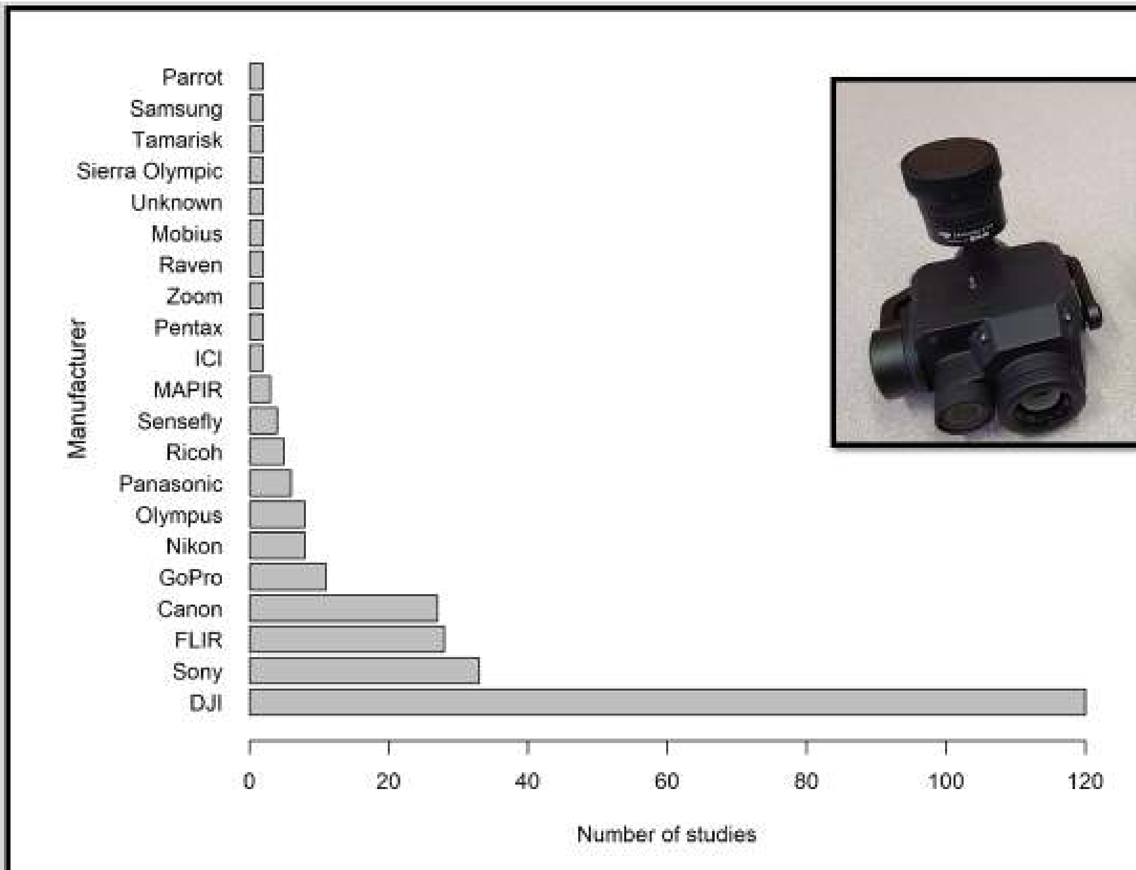

- 126 models from 34 manufacturers

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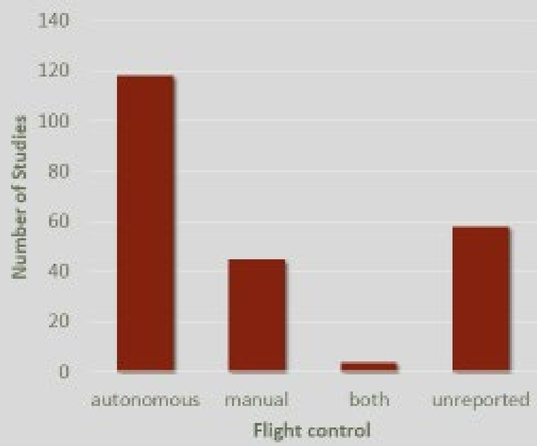
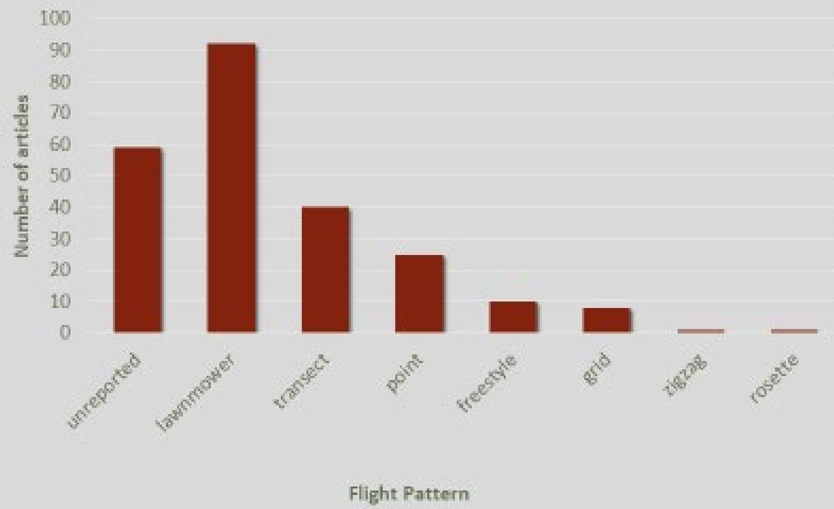
Statistics and study methods

- 36 different analyses
- 61% descriptive





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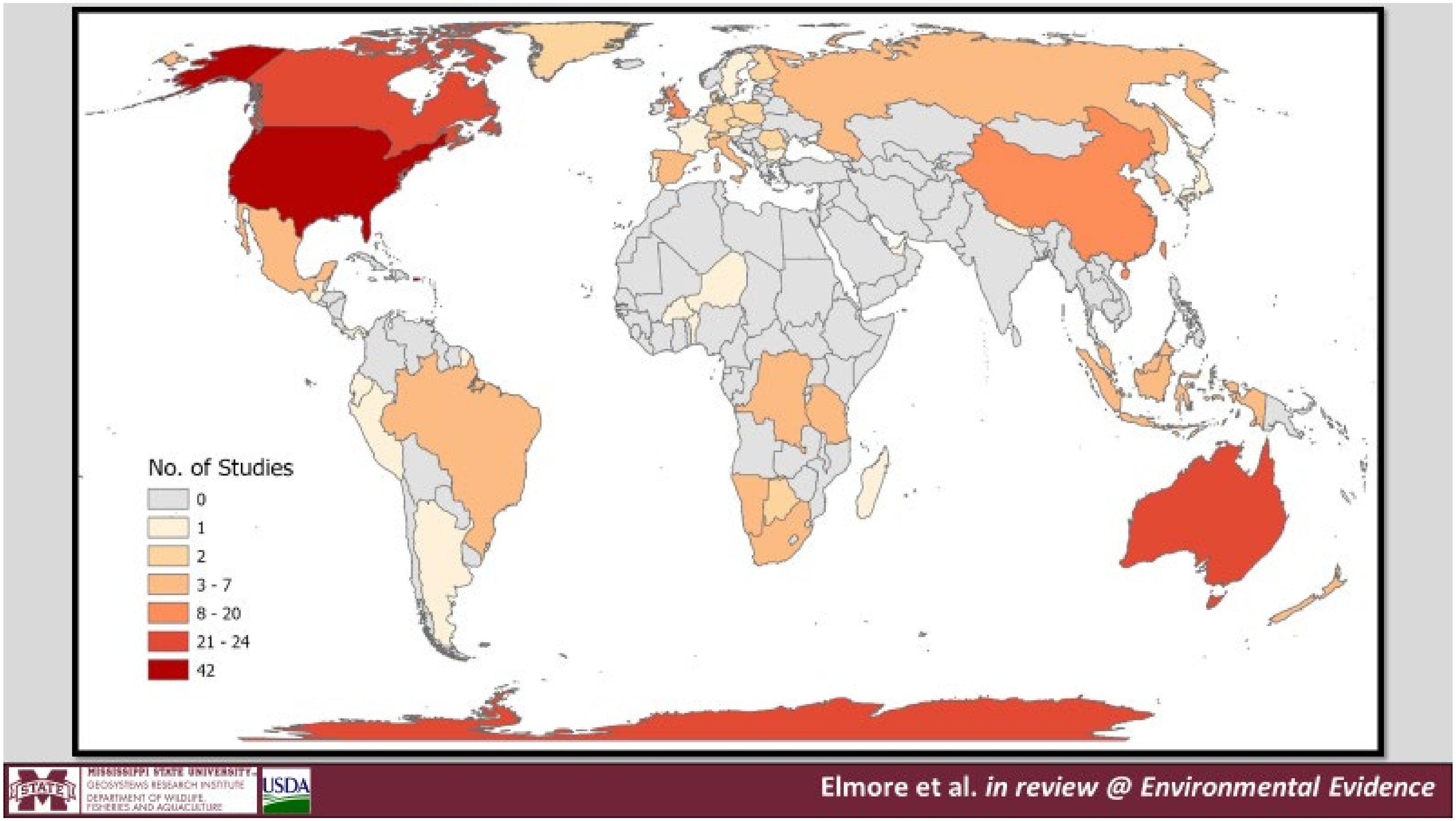
No. of Studies
0
1
2
3 - 7
8 - 20
21 - 24
42
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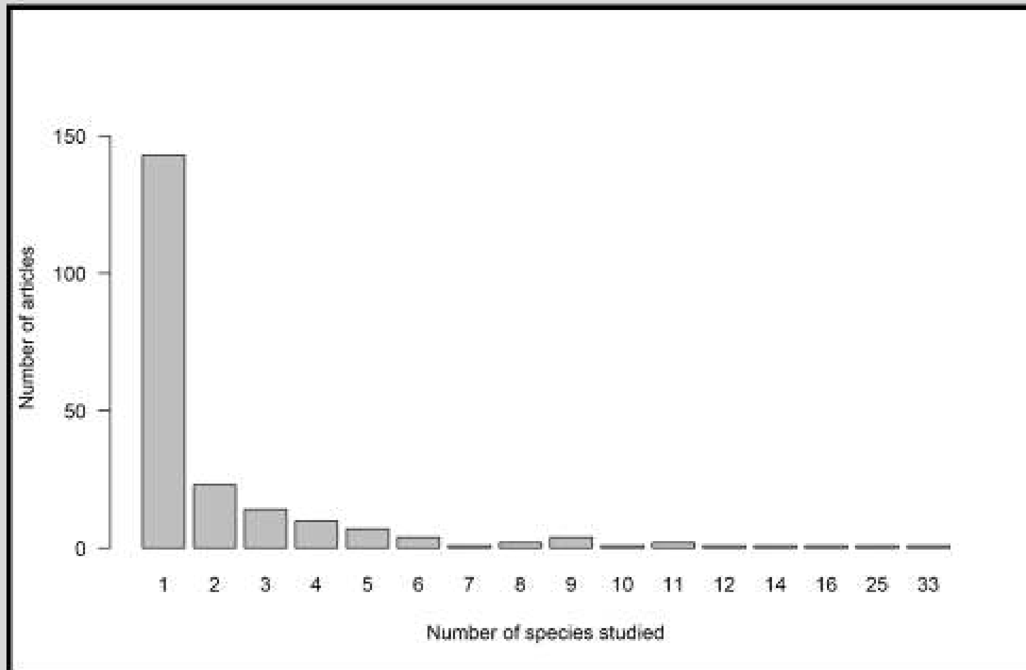
Species

- 187 bird species in 98 studies
- 103 mammal species in 113 studies
- 13 reptile species in 11 studies
- 1 amphibian species in 1 study



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Class	Family	Scientific Name	Common Name	# Studies
Birds	Spheniscidae	*Pygoscelis antarcticus*	Chinstrap Penguin	10
Mammals	Cervidae	*Odocoileus virginianus*	White-tailed Deer	9
Mammals	Phascolarctidae	*Phascolarctos cinereus*	Koala	8
Mammals	Bovidae	*Bos taurus*	Domestic Cattle	8
Birds	Anatidae	*Anas platyrhynchos*	Mallard	8
Birds	Ardeidae	*Ardea alba*	Great White Egret	7
Birds	Spheniscidae	*Pygoscelis adeliae*	Adelie Penguin	7
Mammals	Phocidae	*Halichoerus grypus*	Grey Seal	7
Mammals	Phocidae	*Mirounga leonina*	Southern Elephant Seal	6
Birds	Anatidae	*Anas acuta*	Northern Pintail	5
Birds	Anatidae	*Anas crecca*	Common Teal	5
Birds	Ardeidae	*Ardea cinerea*	Grey Heron	5
Birds	Spheniscidae	*Pygoscelis papua*	Gentoo Penguin	5
Birds	Phalacrocoracidae	*Leucocarbo atriceps*	Imperial Shag	5
Mammals	Hippopotamidae	*Hippopotamus amphibius*	Hippopotamus	5

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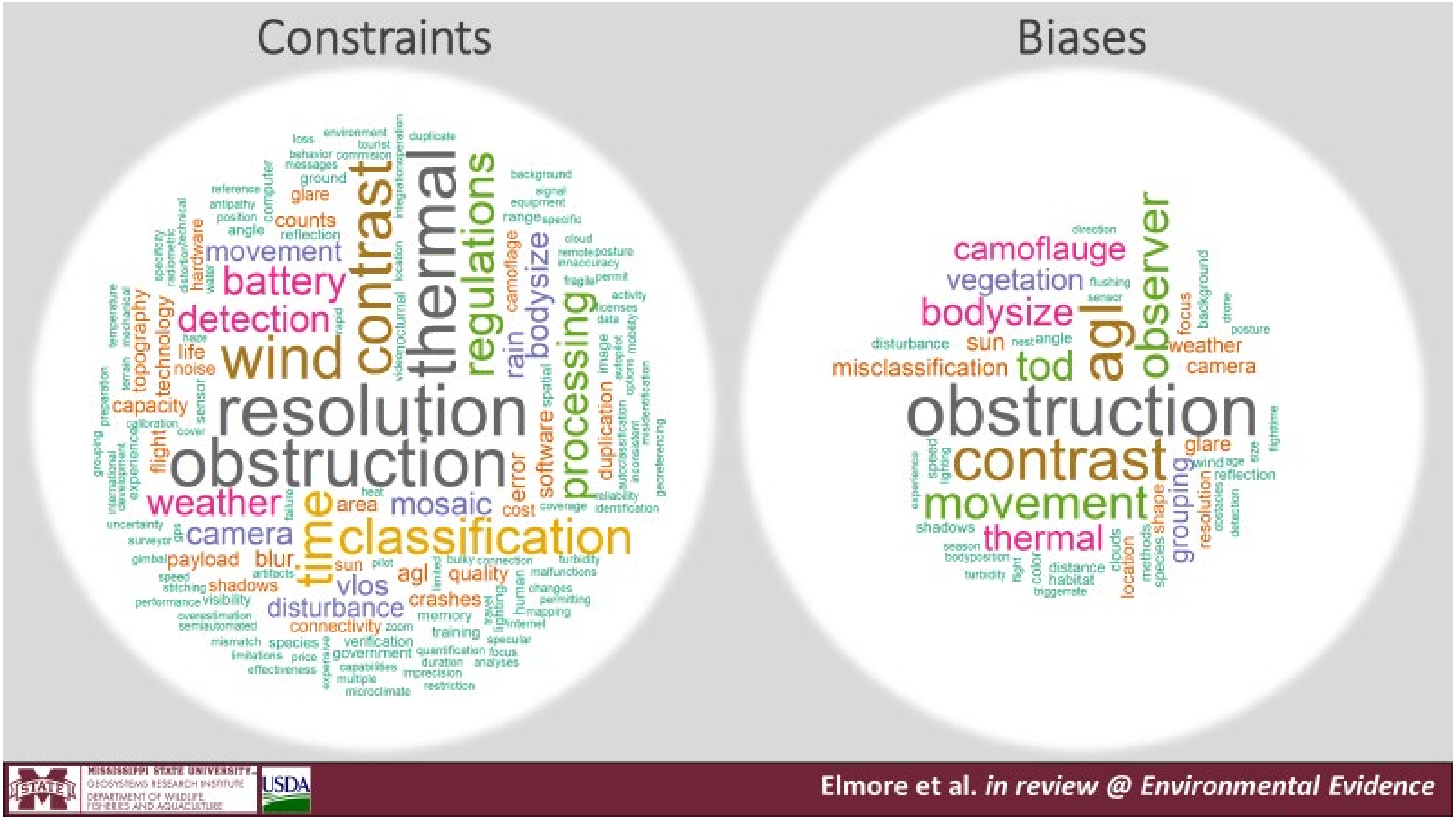
Constraints
Biases
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classification
regulations
processing
battery
detection
movement
bodysize
weather
camera
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error
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vlos
crashes
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payload
blur
shadows
capacity
technology
topography
flight
agl
obstruction
contrast
movement
observer
agl
camoflauge
vegetation
bodysize
misclassification
tod
sun
thermal
grouping
weather
camera
glare
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Knowledge clusters and Gaps

- Single large bodied species using descriptive statistics in open landscapes at small scales
- Best practices for standardized surveys at community level over large areas and how factors affect bias

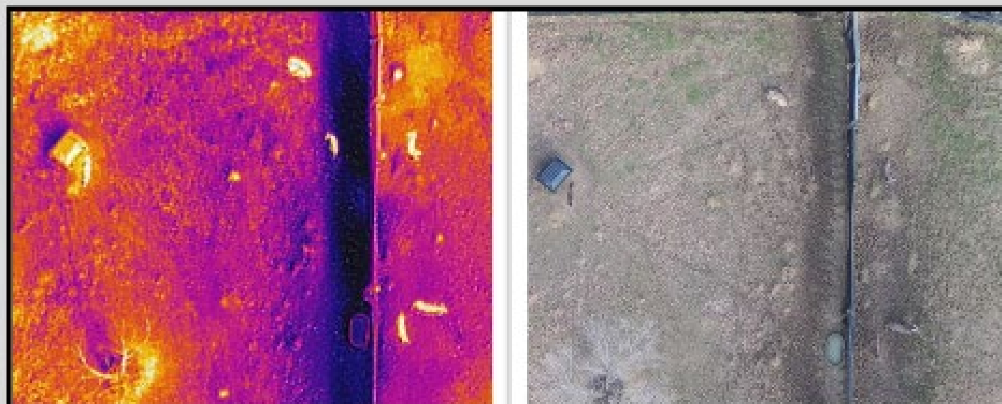

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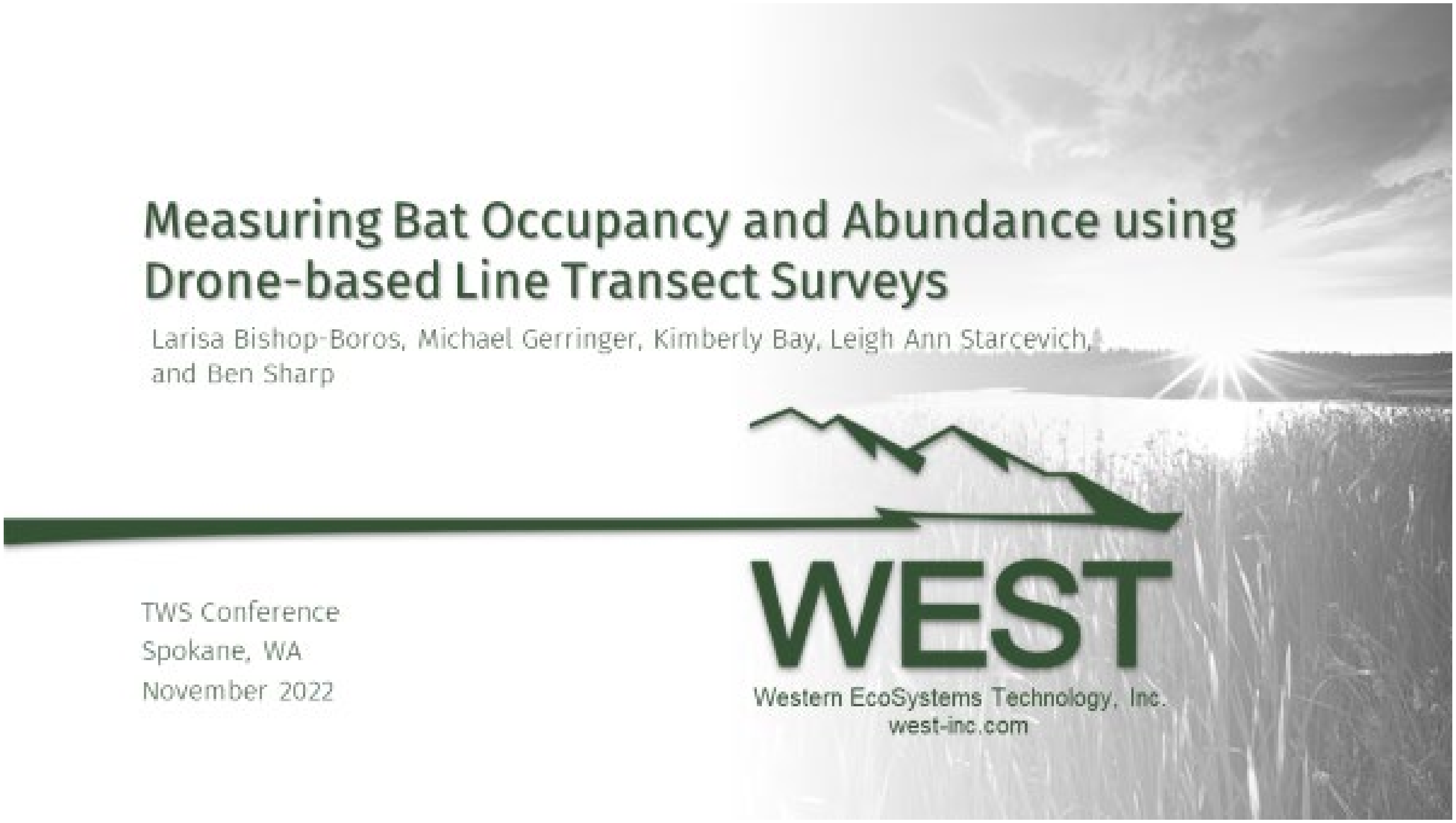
Photo: The Confluence Group jae133@msstate.edu @Elmore_Ecology

Measuring Bat Occupancy and Abundance Using Drone-based Line Transect Surveys

Larisa Bishop-Boros*, Michael Gerringer*, Kimberly Bay*, Leigh Ann Starcevich*, and Ben Sharp*
*Western EcoSystems Technology, Inc.; lboros@west-inc.com

A major challenge of bat management and conservation is the difficulty in estimating the population size for many bat species. Bats are small, volant, nocturnal mammals that roost in trees and caves and are therefore difficult to count and study. Passive acoustic detection methods are commonly used to measure bat activity but are not useful for calculating bat density because individual bats cannot be identified. Therefore, bat population trends, status, and the anthropogenic impact from activities such as energy development are difficult to estimate. The objectives of our research were to improve methods for detecting bats such as sampling to target-specific species, incorporating visual detections, minimizing double counting, and estimating bat abundance rather than limiting inference to occupancy and activity. Additionally, unlike vehicular sampling, our unique approach includes airspace in the rotor-swept zone of wind turbines, increases spatial coverage, and detects non-echolocating bats. In 2020, we pilot tested field methods using a multi-rotor drone equipped with an onboard thermal camera and modified full spectrum acoustic detector that simultaneously recorded bat calls and documented bat passes in thermal videos. In 2021, we collected drone data along 0.5- or 1-km long transects at two operational wind sites and one mitigation site during the fall migration. A passive detector grid was deployed at each site to augment the drone data and inform species composition. We used machine learning algorithms to locate bat thermal detections and applied statistical methods to model bat abundance and calculate trends in species occupancy and abundance over time.


Measuring Bat Occupancy and Abundance using Drone-based Line Transect Surveys
Larisa Bishop-Boros, Michael Gerringer, Kimberly Bay, Leigh Ann Starcevich, and Ben Sharp
TWS Conference
Spokane, WA
November 2022
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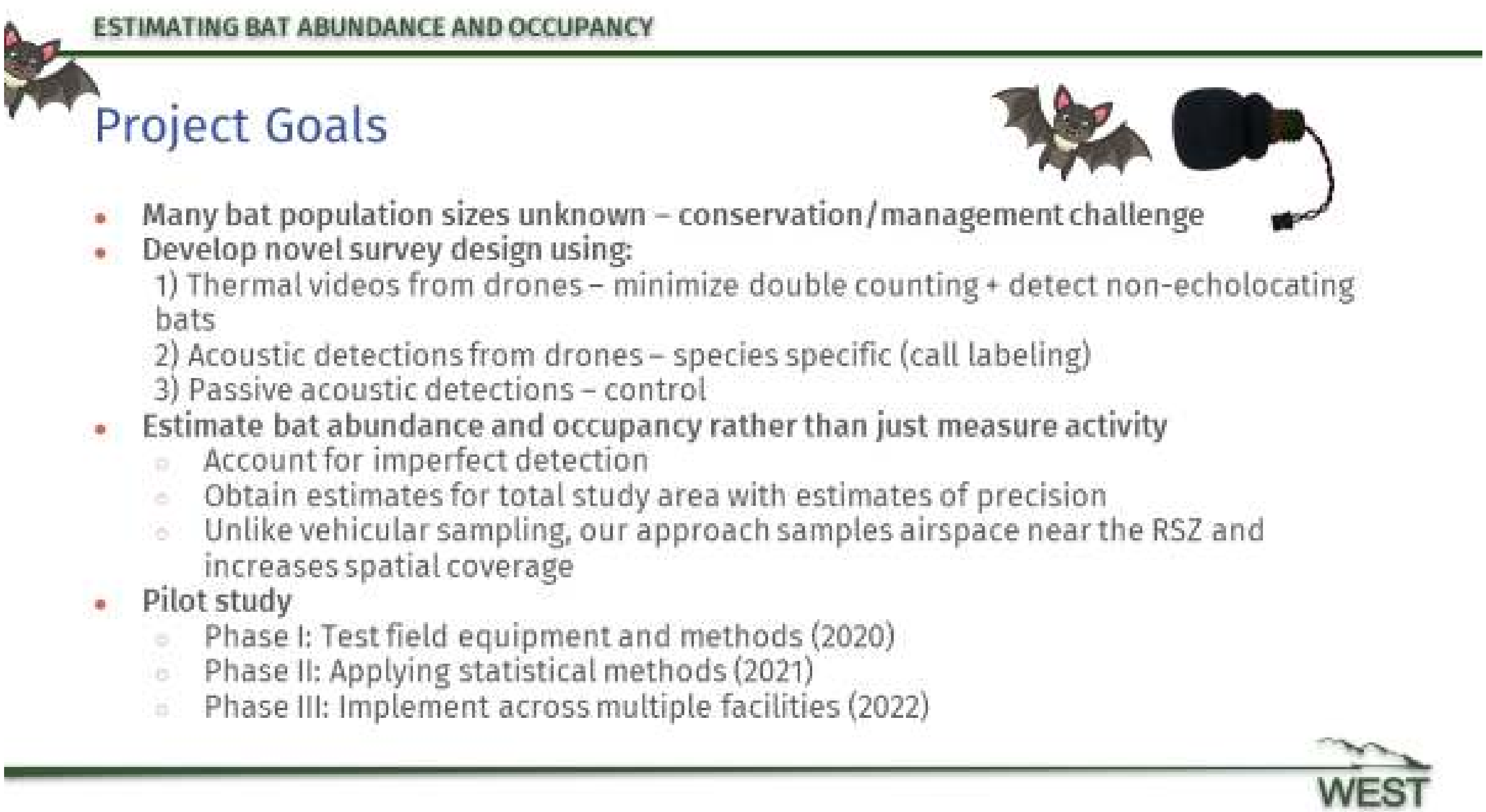
ESTIMATING BAT ABUNDANCE AND OCCUPANCY
Project Goals
• Many bat population sizes unknown – conservation/management challenge
• Develop novel survey design using:
1) Thermal videos from drones – minimize double counting + detect non-echolocating bats
2) Acoustic detections from drones – species specific (call labeling)
3) Passive acoustic detections – control
• Estimate bat abundance and occupancy rather than just measure activity
○ Account for imperfect detection
○ Obtain estimates for total study area with estimates of precision
○ Unlike vehicular sampling, our approach samples airspace near the RSZ and increases spatial coverage
• Pilot study
○ Phase I: Test field equipment and methods (2020)
○ Phase II: Applying statistical methods (2021)
○ Phase III: Implement across multiple facilities (2022)
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Equipment

- Multi-rotor DJI Matrice 210 drone
- Carrying a thermal camera:
  - 640x512 DJI FLIR Zenmuse XT2
  - a 25-mm (1.1-in) lens
  - frame rate of 30 hertz
  - weather resistant case

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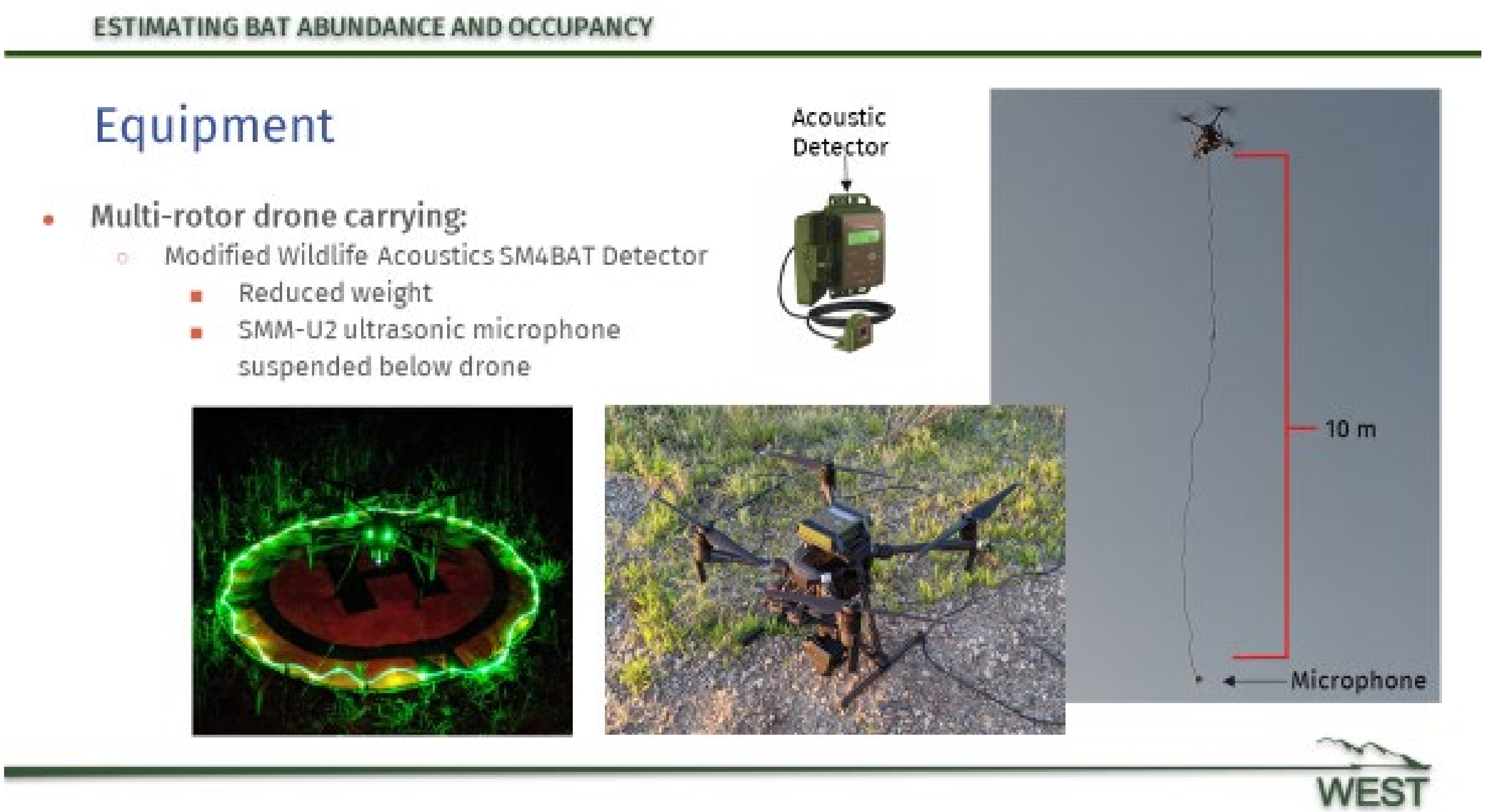
ESTIMATING BAT ABUNDANCE AND OCCUPANCY
Equipment
Multi-rotor drone carrying:
Modified Wildlife Acoustics SM4BAT Detector
Reduced weight
SMM-U2 ultrasonic microphone suspended below drone
Acoustic Detector
10 m
Microphone
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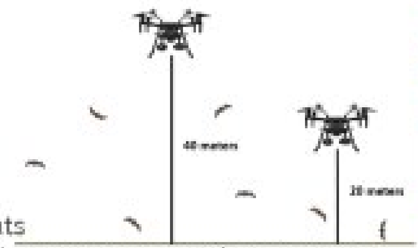
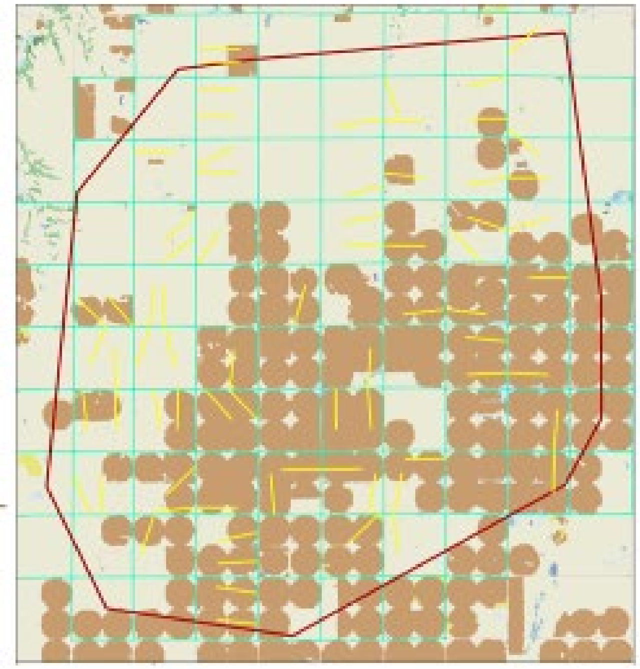
Survey Methods

- Study area
  - 72 1-km transects (2 min 40 sec flight/transect)
  - 7 visits (504 transect flights)
- Survey planning: Transects located where feasible
  - Line of sight
  - Tree height
  - Houses
  - Power lines



- Drone Methods
  - Flew transects faster than bats
  - Transects flown at either 20 (~30° camera angle) or 40 meters above ground (~40° angle)
  - Recorded thermal videos and acoustic data along transects
  - Recorded wind speed and temperature at time of flight
  - Computed dominant land cover type per transect
  - Didn't fly if wind speed > 9 mph



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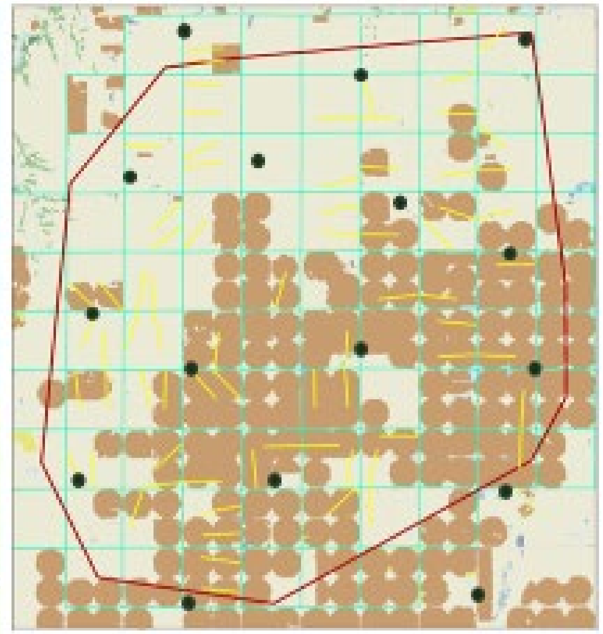
Passive Acoustic Methods

- Grid of 16 stationary detectors established at each site
  - 2.3 – 2.5 mi (based on average flight speed of Lasiurids at 27.7 kph) where land access allowed
- Acoustic data collected throughout late summer maternity and early fall migratory season
  - July – August
- Purpose
  - Agency buyoff
  - Serve as validation of drone data
  - Aid in modeling species-level abundance



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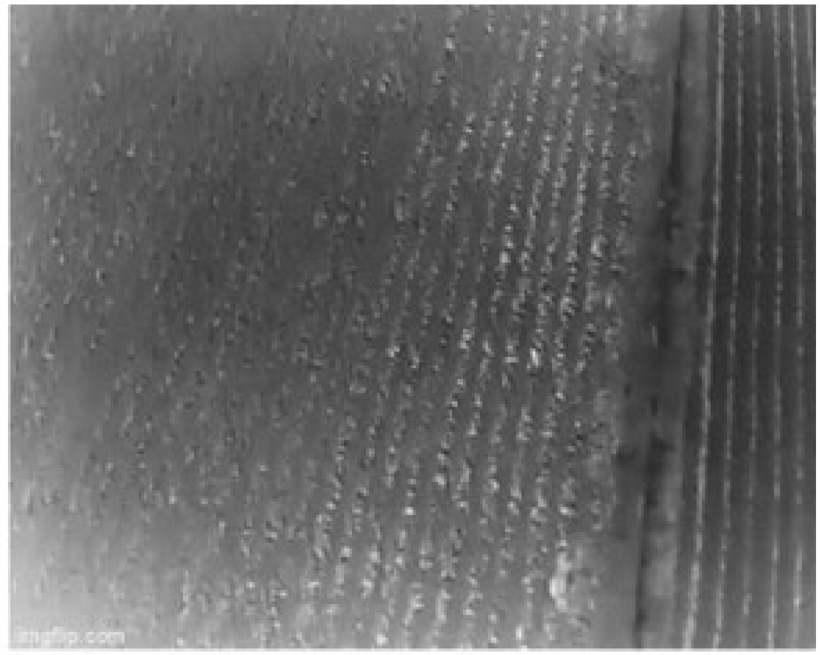
Thermal Camera Video Review Process

- Manual review to locate bat thermal detections
  - Record each bat pass detected



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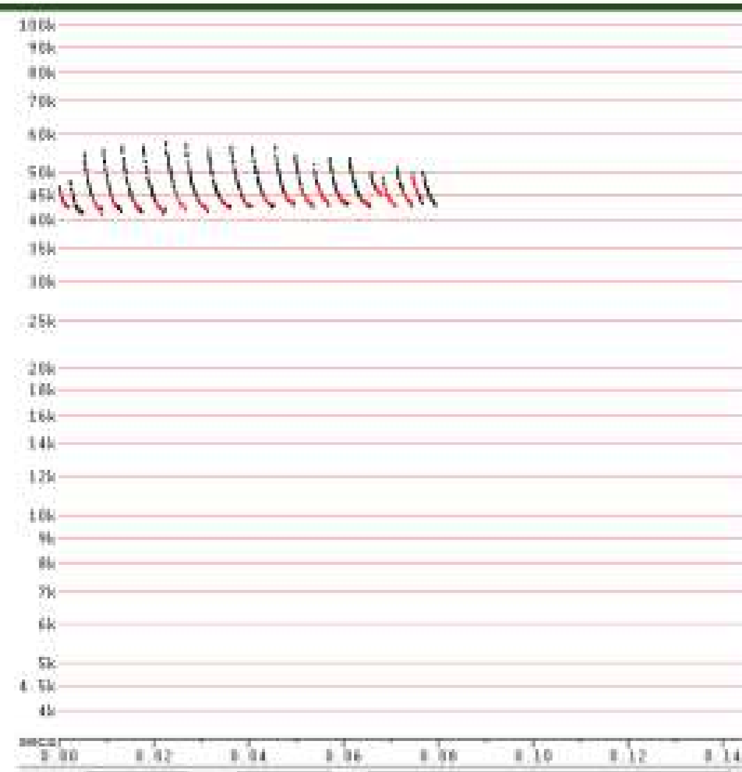
Call Labeling Methods

- Full spectrum acoustic data converted to ZC
- Data manually labeled in AnaLook to species, species group, or frequency group (LF or HF) as call quality allowed.



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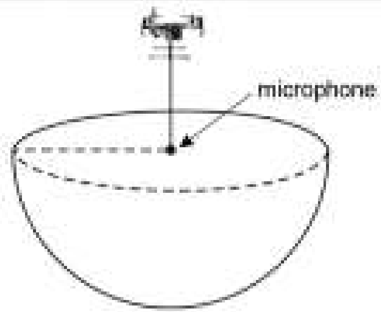
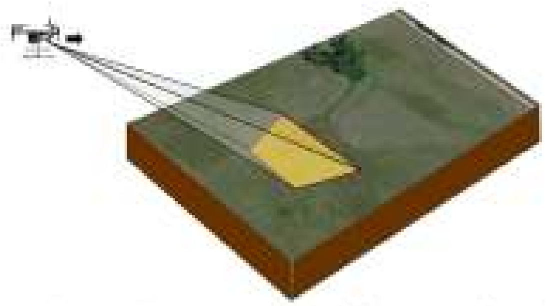
Survey Effort

UAS Start Date	UAS End Date	Flight Height	Transect Length (km)	Total Flights	Unique Transects	Acoustic Coverage* (km^2)	Video Coverage* (km^2)
7/19/2021	8/31/2021	20	1	245	35	1.40	0.91
		40	1	259	37	1.48	1.41

*area



Detector: Representation of the approximate shape of the ultrasonic microphone coverage based on an assumed 20-meter detection range



Camera: Representation of the approximate shape of the thermal coverage

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Analysis Methods

- **Model**
  - Status: model by land cover category
    - Occupancy: Presence/absence accounting for imperfect detection
    - Abundance: Conditional on occupancy, model Poisson count (Dail and Madsen 2010)
  - Detection: a function of wind speed, temperature, and flight height
- **Estimate density: Obtain estimates of abundance and divide by the total area surveyed on each visit**
  - Weight by land cover class
- **Extrapolate density to entire study area to estimate abundance**
- **Use acoustic detections to estimate**
  - Abundance by species
  - Abundance by frequency class

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Land Cover

Land Cover Category	Proportion of Study Area	Proportion of Sample
Developed, Open Space	0.02	
Grassland/Herbaceous	0.53	0.47
Cultivated Crops	0.44	0.53
Other	0.01	

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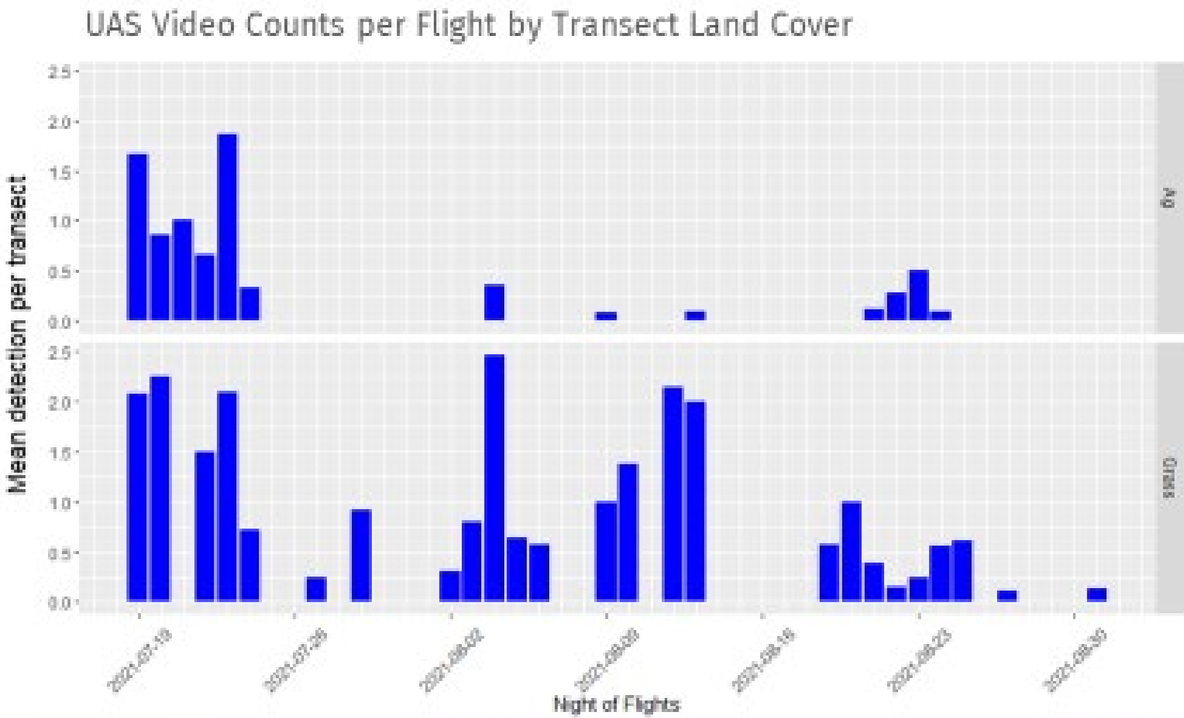

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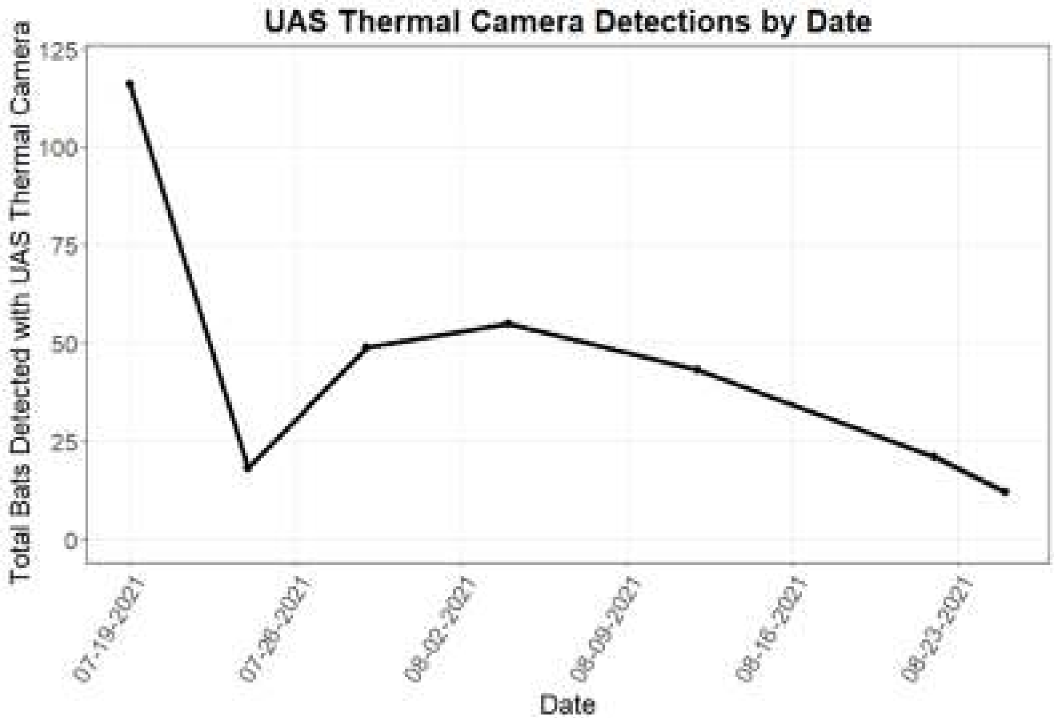

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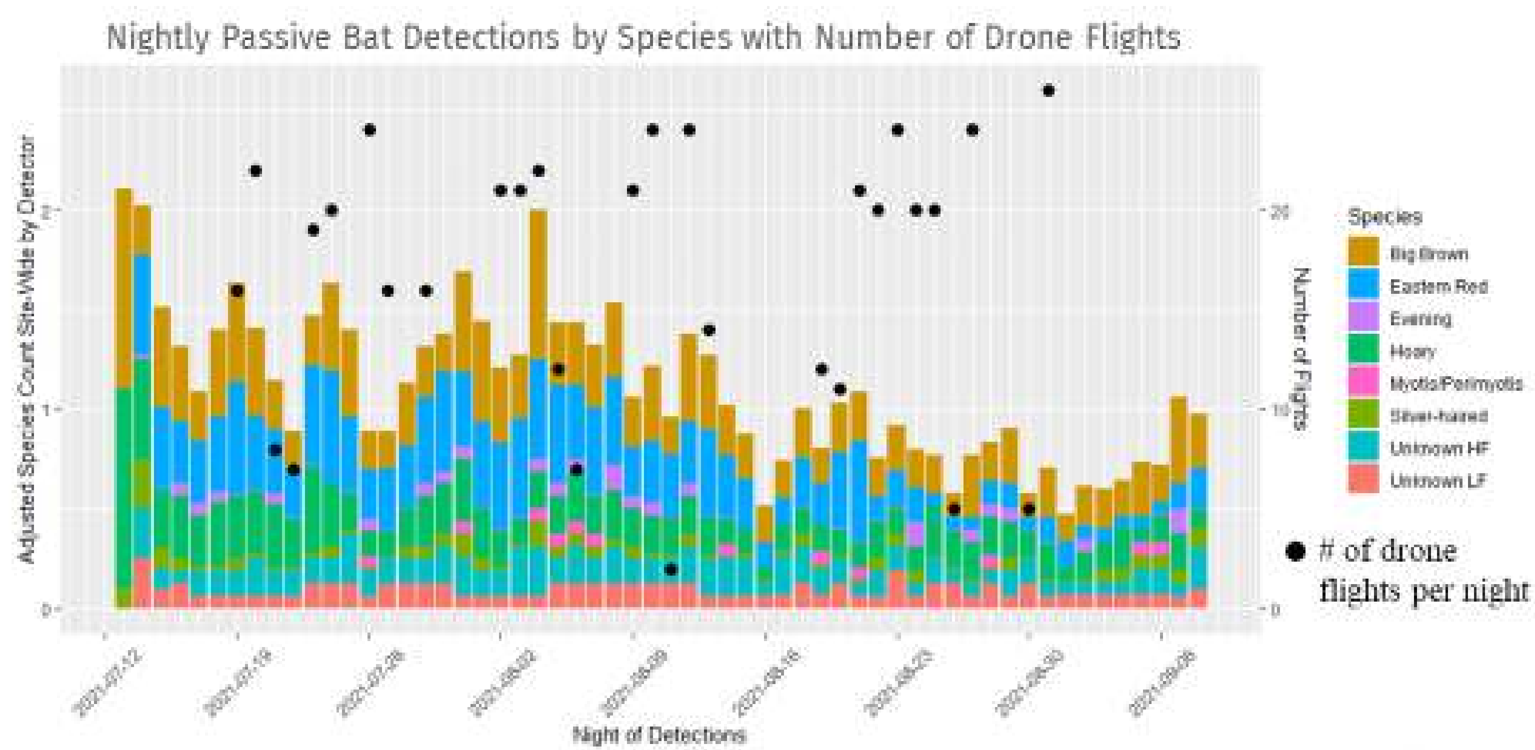

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Species	Drone Video	Drone Acoustic	Passive Acoustic on Drone Flight Nights	Passive Acoustic on All Nights
Big Brown	-	26	138	256
Big Brown/Silver Haired	-	6	-	-
Eastern Red	-	22	151	251
Evening Bat	-	0	14	27
Hoary	-	0	97	173
Silver Haired	-	0	17	38
Myotis/Perimyotis	-	0	6	12
Unknown HF	-	7	63	116
Unknown LF	-	0	46	81
Total Unique Passes	314	61	532	954

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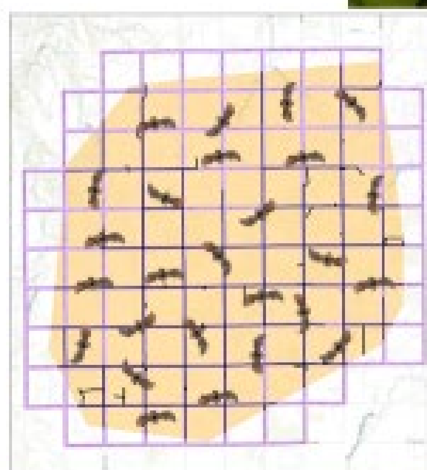
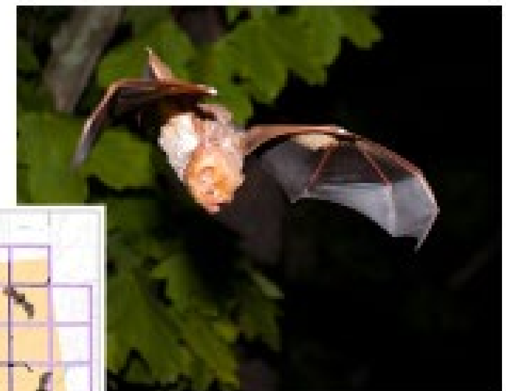
Site Occupancy Rates and Detection Probabilities

- Occupancy rate at Visit 1: 0.59
  - 95%-CrI: (0.48, 0.70)
- Detection rate: 0.95
  - 95%-CrI: (0.88, 0.99)
  - Temperature and wind speed not significant predictors





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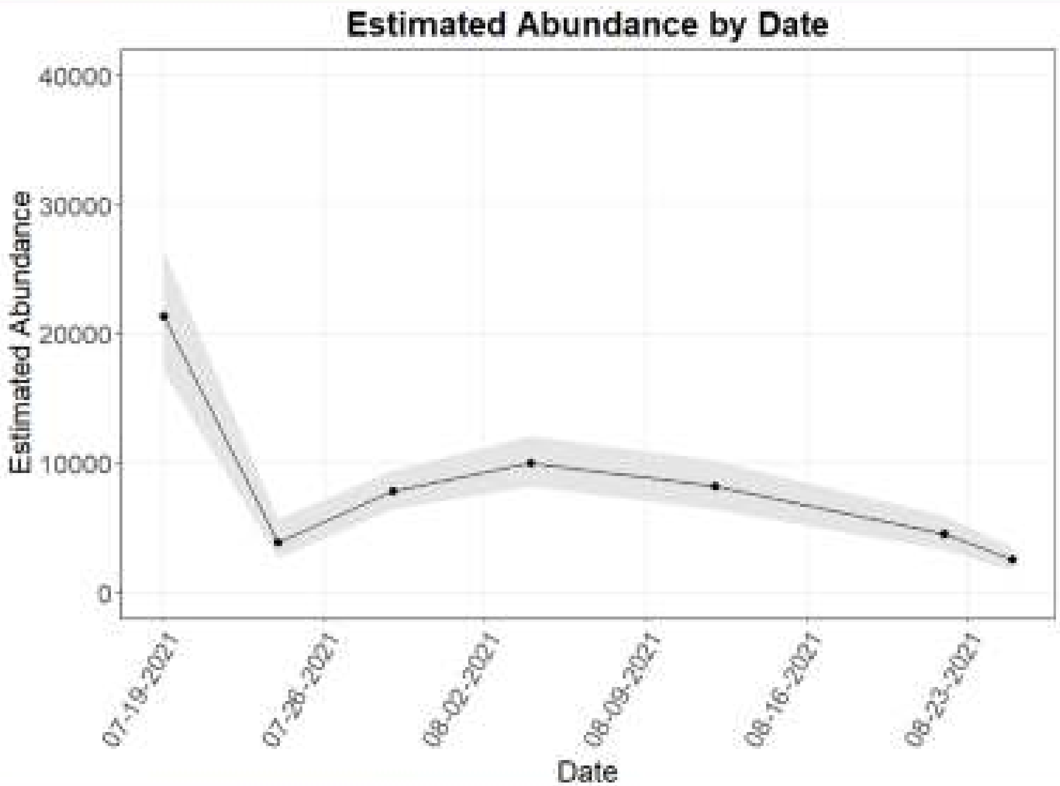

- Based on thermal camera

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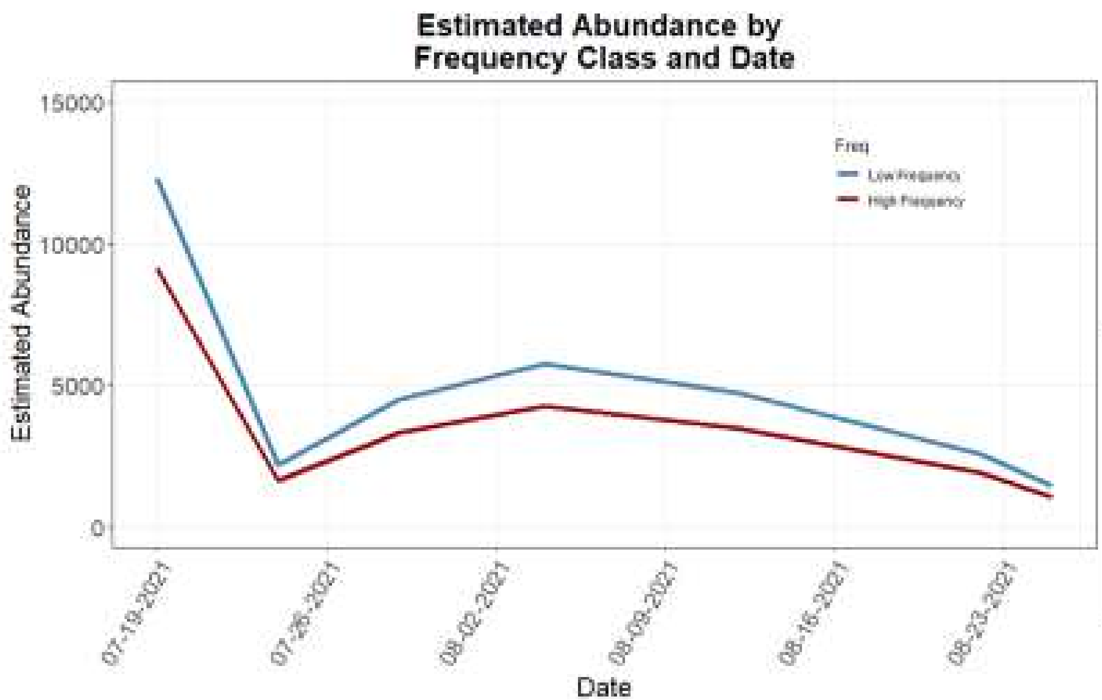

- Camera data with frequency groups informed by passive detectors

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Discussion

- Preliminary results indicate that estimates of abundance and occupancy can be obtained with reasonable precision using the survey and analysis methods we proposed
  - Trends in occupancy and abundance
  - Species-level estimation with acoustic detections
  - Temporal replication not needed
  - Land cover was potential predictor of occupancy and abundance
- Improvements for Phase III
  - Improve detection rates for drone acoustic detectors
    - Spare microphones to ensure enduring microphone sensitivity
    - Passive acoustic detectors won't be needed in the future
  - Temporal replication for trend estimates and assessment of consistency of estimates over time
- Recommendations based off pilot studies

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Thank You!

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lstarcevich@west-inc.com for statistical questions

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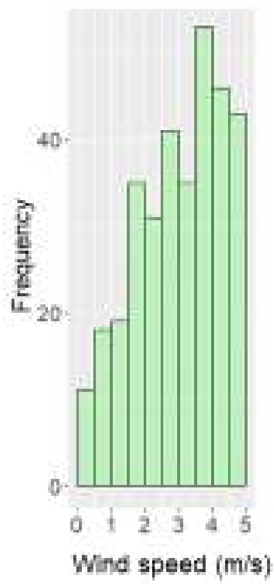
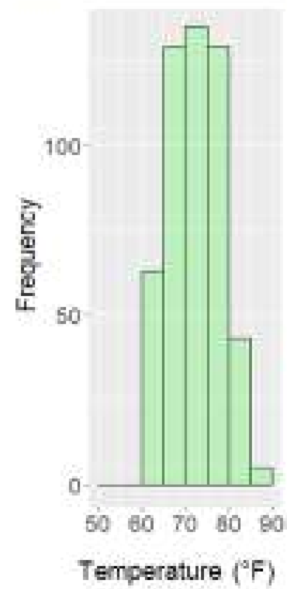
Detection Covariates: Wind Speed, Temperature, Flight Height





- Covariates for wind speed, temperature, and flight height were not significant

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Abundance Estimates

Visit	Bat Video Count	Transect Density (Bats/sq km)	Transect Density 95%-CrI Lo	Transect Density 95%-CrI Hi	Est Abundance	Est Abundance 95%-CrI Lo	Est Abundance 95%-CrI Hi
1	116	119	95	148	21336	17050	26481
2	18	21	15	32	3832	2620	5678
3	49	44	36	53	7836	6380	9502
4	55	56	46	67	9965	8114	12032
5	43	46	36	57	8203	6403	10177
6	21	25	18	33	4470	3242	5959
7	12	14	9	20	2477	1648	3488

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Abundance By Species/Frequency Group

Visit	Big Brown	Eastern Red	Hoary	Evening	Myotis/ Perimyotis	Silver Haired	Total LF	Total HF
1	5802	5632	3863	588	269	851	12287	9103
2	1038	1008	691	105	48	152	2198	1629
3	2122	2060	1413	215	98	311	4494	3329
4	2712	2633	1806	275	126	398	5744	4256
5	2224	2159	1481	225	103	326	4710	3489
6	1217	1181	810	123	56	179	2576	1909
7	670	651	446	68	31	98	1419	1052

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