Integrating Technology Into Wildlife Surveys

Sally E. Yannuzzi

INTEGRATING TECHNOLOGY INTO WILDLIFE SURVEYS

By

Sara Elena Yannuzzi
Bachelor of Science, University of Maryland 2014
Master of Science, West Virginia University 2018

A Dissertation

Submitted to the Graduate Faculty

of the

University of North Dakota

In partial fulfillment of the requirements

For the degree of

Doctor of Philosophy

Grand Forks, North Dakota

December

2023

This dissertation, submitted by Sara Yannuzzi in partial fulfillment of the requirements for the Degree of Doctoral of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

Dr. Susan Ellis-Felege

Dr. Mark Kaemingk

Dr. Brian Darby

Dr. Gregory Vandeberg

Dr. Rebecca Romsdahl

This dissertation is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

Chris Nelson
Dean of the School of Graduate Studies

Date

PERMISSION

Title	Integrating Technology into Wildlife Surveys
Department	Biology
Degree	Doctor of Philosophy

In presenting this dissertation in partial fulfillment of the requirements for a graduate degree from the University of North Dakota, I agree that the library of this University shall make it freely available for inspection. I further agree that permission for the extensive copying for scholarly purposes may be granted by the professor who supervised by dissertation work or, in her absence, by the Chairperson of the department or the dean of the School of Graduate Studies. It is understood that any copying or publication or other use of this dissertation or part thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of North Dakota in any scholarly use which may be made of any material in my dissertation.

Sally Yannuzzi
October 15, 2023

TABLE OF CONTENTS

LIST OF FIGURES

Chapter II

Chapter III

Chapter IV

Chapter V

LIST OF TABLES

Chapter III

Chapter V

ACKNOWLEDGMENTS

It likely comes as little surprise that completing a PhD takes a small village, or maybe a medium-sized village like Grand Forks. Amidst a career shift and a return to research, I found myself stepping into a snow globe in early January 2020 and despite it being the coldest city in the lower 48, I found a community of the warmest people to guide my academic and life journey.

To Susan and Chris Felege, thank you for not only supporting me through many days afield (including hot coffee and plentiful field access), surely countless hours spent reviewing and editing papers, mentorship, and acquainting me to drones and PCM, but also for introducing David and I to the world of ice fishing and welcoming us North Dakota-style.

I am sincerely grateful for the guidance provided by my graduate committee, Drs. Gregory Vandeberg, Rebecca Romsdahl, Brian Darby, and Mark Kaemingk. I would also like to thank Thread, Microsoft, and the North Dakota Department of Transportation for financial support. Thank you to the Knudsons, Flecks, Feleges, Hansens, and Xcel Energy for land access. I would like to express my sincere gratitude to the team of technicians and volunteers who spent long hours with stinky carcasses walking back and forth: Amalie Jorgensen, Lindsey Kallis, Nick Hill, Charles McDunn, Cailey Isaacson, and Gaddum Reddy.

Thank you to my friend and lab mate, Taylor Linder, for being a sounding board, support system, mentor, and fellow duck head. To Kelsey Morin, Dorothy Daulton, and Julia Hampton, thank you for the long dog walks and time spent at The Other Half writing and giggling (probably more of the latter).

Probably not thanked often enough in the acknowledgements section of graduate work are people and places that supported your mental and social well-being throughout your academic tenure. I'd like to acknowledge my hunting crew (Taylor, Phil, David, Jade, and Grebe) who gave new meaning to work hard, play hard, I will cherish the mental breaks spent driving around eastern North Dakota in search of greenheads in gold fields, and watching the sunrise while pintails swarmed overhead with our faithful red dogs by our sides. Thank you to Grand Forks Broomball, Half Brothers Brewery, and Buffalo Wild Wings for the many evenings spent laughing with friends over a good brew. Thank you to my dog gal pals, Lizzi Bonczek and Catrina Terry, for your companionship in the training of good dogs and search for grouse (and of course, academic talk).

To Jared, thank you for teaching me the art of flying drones, 2 AM wake up calls to drive to the field, and helping David replace our window. To Evelyn, thank you for your steadfast friendship, excellent cooking, and holding down the fort while we were field bound.

To my family, husband, David, and our furry companions Rowen, Grebe, Red, and Louie, thank you all for your support and patience with me when I was overwhelmed, and supporting my most ridiculous ideas and adventures. Who knew we'd end up liking North Dakota so much?

ABSTRACT

Technology is rapidly improving and being incorporated into field biology, with survey methods such as machine learning and uncrewed aircraft systems (UAS) headlining efforts. UAS paired with machine learning algorithms have been used to detect caribou, nesting waterfowl and seabirds, marine mammals, white-tailed deer, and more in over 19 studies within the last decade alone. Simultaneously, UAS and machine learning have also been implemented for infrastructure monitoring at wind energy facilities as wind energy construction and use has skyrocketed globally. As part of both pre-construction and regulatory compliance of newly constructed wind energy facilities, monitoring of impacts to wildlife is assessed through ground surveys following the USFWS Land-based Wind Energy Guidelines. To streamline efforts at wind energy facilities and improve efficiency, safety, and accuracy in data collection, UAS platforms may be leveraged to not only monitor infrastructure, but also impacts to wildlife in the form of both pre- and post-construction surveys.

In this study, we train, validate, and test a machine learning approach, a convolutional neural network (CNN), in the detection and classification of bird and bat carcasses. Further, we compare the trained CNN to the currently accepted and widely used method of human ground surveyors in a simulated post-construction monitoring scenario. Last, we establish a baseline comparison of manual image review of waterfowl pair surveys with currently used ground surveyors that could inform both pre-construction efforts at energy facilities, along with long-standing federal and state breeding waterfowl surveys. For the initial training of the CNN, we collected 1,807 images of bird and bat carcasses that were split into 80.0% training and 20.0% validation image sets. Overall detection was extremely high at 98.7%. We further explored the dataset by evaluating the trained CNN's ability to identify species and the variables that impacted identification. Classification of species was successful in 90.5% of images and was associated with sun angle and wind speed. Next, we performed a proof of concept to determine the utility of the trained CNN against ground surveyors in ground covers and with species that were both used in the initial training of the model and novel. Ground surveyors performed similar to those surveying at wind energy facilities with 63.2% detection, while the trained CNN fell short at 28.9%. Ground surveyor detection was weakly associated with carcass density within a plot and strongly with carcass size. Similarly, detection by the CNN was associated with carcass size, ground cover type, visual obstruction of vegetation, and weakly with carcass density within a plot. Finally, we examined differences in breeding waterfowl counts between ground surveyors and UAS image reviewers and found that manual review of UAS imagery yielded similar to slightly higher counts of waterfowl.

Significant training, testing, and repeated validation of novel image data sets should be performed prior to implementing survey methods reliant upon machine learning algorithms. Additionally, further research is needed to determine potential biases of counting live waterfowl in aerial imagery, such as bird movement and double counting. While our initial results show that UAS imagery and machine learning can improve upon current techniques, extensive follow-up is strongly recommended in the form of proof-of-concept studies and additional validation to confirm the utility of the application in new environments with new species that allow models to be generalized. Remotely sensed imagery paired with machine learning algorithms have the potential to expedite and standardize monitoring of wildlife at wind energy facilities and beyond,

improving data streams and potentially reducing costs for the benefit of both conservation agencies and the energy industry.

CHAPTER I BACKGROUND AND LITERATURE REVIEW

To the general public, awareness of birds and bats largely focuses on yard stewardship activities, nuisance interactions, and zoonotic diseases (Clergeau et al. 2001, Belaire et al. 2015, Hoffmaster et al. 2016). While not always held in high regard by the public, birds and bats offer a variety of goods and ecosystem services that aid in human and environmental welfare. Birds provide more obvious aesthetic, cultural, recreational, and economic services through hunting opportunities and bird watching (Grado et al. 2011, Belaire et al. 2015, Bagstad et al. 2019), but they also provide humans with a number of provisioning services, including meat for consumption and feathers for use in apparel, bedding, jewelry, and art (Whelan et al. 2008, Green and Elmberg 2014, Whelan et al. 2015). Birds offer scavenging services, working as decomposers aiding in nutrient cycling (Hiraldo et al. 1991, DeVault et al. 2003, Wenny et al. 2011). Both birds and bats work to regulate pest arthropods, disperse seeds, and pollinate plants (Maas et al. 2016). This ultimately improves plant growth, increasing agricultural production of food and timber crops, and of non-cultivated plants and trees that improve air, soil, and water quality (De Deyn et al. 2008, Whelan et al. 2008, Barrios et al. 2018). Despite all the seen and unseen benefits birds and bats provide to both the natural and developed environment, the relationship between humans versus birds and bats is far from mutualistic and is teetering towards parasitic in the last century.

A recent study exposed that North America has lost over 30% of its bird population in the last 50 years, with a large portion of them being native grassland birds (Rosenberg et al. 2019). The devastating loss of these ecosystem benefactors is further compounded by rapid declines in bat populations due to the spread of the fatal disease white-nose syndrome and wind turbine-related mortalities (Frick et al. 2010, Frick et al. 2017, Rodhouse et al. 2019). Concerns for birds and bats has increased in North America by creating alarm and a call to action to amend these losses. Such widespread concern has led to an influx in the need for wildlife monitoring to support processes of adaptive management, in which the efficacy of a wildlife management strategy is evaluated over a period of time and modified in response to results gleaned from monitoring efforts (Ringold et al. 1996, Gibbs et al. 1999).

Standardized wintering and breeding ground and aerial surveys of bird population indices have long been instituted for informing regulations, including the Mid-Winter Waterfowl Inventory (MWI), the Waterfowl Breeding Population and Habitat Survey (BPOP), and the North American Breeding Bird Survey (NABBS). However, data quality can be negatively impacted due to inconsistent surveying strategies and survey areas, coverage restrictions due to time and money, observer bias and counting error, and the availability of a pilot and weather interfering with timing of surveys (Eggeman and Johnson 1989, Smith 1995, Heusmann 1999, Kingsford and Porter 2009). Traditional ground surveying methods can also be expensive, ultimately impeding the quality of the monitoring and research being performed through lower-quality equipment, smaller sample sizes, and less experienced or fewer surveyors than needed, not to include any additional essential equipment such as transmitters (Jones et al. 2006, Koh and Wich 2012). To make traditional wildlife monitoring as efficient and effective as possible, surveyors that are experts in their field are necessary to obtain the best data possible. Yet unfortunately, even highly skilled biologists are not exempt from error and are prone to surveyor fatigue, which can cause data errors, especially when environmental and habitat conditions make monitoring efforts increasingly difficult (Cordts et al. 2002, Fleming and Tracey 2008, Habib et al. 2012, Ransom 2012, Ogden 2013, Chretien et al. 2015). As such, there is a need to re-examine traditional monitoring methods, both ground and aerial, and harness the power of emerging technologies to increase and improve wildlife population data feeds vital to producing high quality repeatable procedures and regulations.

There has been an increasing need for the development of sustainable, environmentally friendly energy production with a growing global population and heightening concerns about climate change (Veers et al. 2019). While there has been a suite of energy solutions developed, including solar power, geothermal, wave power, and more, wind has become the frontrunner in the race for green energy. Within a short time, wind energy has been implemented at a broad-scale and is expected to increase by ten times prior to the year 2050 (DNV GL 2018, Veers et al. 2019). Current global annual investment in wind energy is $100 billion (US) and will soon become one of the world's big energy sources (DNV GL 2018, Veers et al. 2019). It is with little surprise that the global energy push is towards wind. Not only is wind energy renewable, it is also broadly available, low cost, and has a minute pollutant footprint (Veers et al. 2019), ultimately offering both public and environmental health benefits by way of cleaner air (Campbell-Lendrum and Corvalan 2007, Chan 2009). The push for wind energy in the United States has largely stemmed from this global movement and increased technological developments (DNV GL 2018). The integration of energy, engineering, and science sectors is instrumental to the enhancement of wind power and technology (Veers et al. 2019).

Like any large-scale anthropogenic structure, siting and impacts to the surrounding environment and community must be taken under consideration. This is particularly true for the potential impacts that wind energy infrastructure may have on surrounding wildlife communities, such as birds and bats, through direct collision-related mortalities, displacement, and habitat fragmentation (Kuvlesky et al. 2007, Kiesecker et al. 2011, Shaffer and Buhl 2015). As such, federal laws protecting wildlife and the environment, like the National Environmental Policy

Act, the Migratory Bird Treaty Act, the Endangered Species Act, and the Bald and Golden Eagle Protection Act, require industry to adhere to a set of compliance standards and perform both pre- and post-construction mortality monitoring (PCMM; USFWS 2012). This poses a challenge to energy companies, particularly in such sensitive and keystone environments found in North Dakota.

A region integral to both migratory and breeding birds, North Dakota has subsequently been coined as part of "North America's Duck Factory" (Johnson et al. 2005, Mahlum and Perez 2012). But less obvious is the economic impact that bats can have on an area that is so heavily reliant on the agricultural economy. In North Dakota alone, there are 11 species of bats present (Nelson et al. 2015). Past research has shown that through ecosystem services such as the removal of pest arthropods, a single species of bat has saved rice crop losses in excess of $1.2 million/year (Wanger et al. 2014, Maas et al. 2016). Even beyond pest reduction, bats have proven to stimulate pollination services comparable to $13 million/year (Bumrungsri et al. 2009, Maas et al. 2016). In a state where the wildlife, agricultural, and energy sectors are dominant economic powerhouses (Baltezore and Leitch 1992, Coon et al. 2014, Ndembe et al. 2019), it is vital to North Dakota's economy and success in both the wildlife and energy industries to factor in wind farm placement and wildlife monitoring efforts to provide as much wind energy as possible while minimizing impacts to wildlife. On a national scale, large population declines in cave bat species caused by white-nose syndrome has resulted in the federal uplisting or proposed listing of several bat species. This further supports the need for refined and efficient species monitoring.

Attempts to monitor and minimize wildlife impacts are usually accomplished through a variety of surveys. There are typically three tiers of pre-construction monitoring at land-based wind energy centers: preliminary site evaluation (tier 1), site-specific evaluation (tier 2), and risk assessment (tier 3; Katzner et al. 2016). Tier 1 involves a review of existing habitat and species data for the region encompassing the potential siting area and follows with a decision on whether to proceed relative to a cost-benefit analysis. Tier 2 focuses more specifically on the siting area, determining where high and low value bird and bat species and habitats exist. Tier 3 includes more rigorous scientific studies to determine such variables as species abundance and distribution through methods like point count surveys, acoustic monitoring surveys, and subsequent risk modeling (Katzner et al. 2016). Despite this, there are no standardized methods for pre-construction surveys and most models are bald eagle (*Haliaeetus leucocephalus*) and golden eagle (*Aquila chrysaetos*) specific, neglecting the importance of other avian species and bats (Katzner et al. 2016).

If findings from pre-construction surveys determine that a project should move forward, federally required post-construction surveys occur for at least one year following construction, and typically include standardized carcass searches, searcher efficiency trials (SEEFs), and carcass persistence trials (CPTs) (USFWS 2012). SEEFs and CPTs are both bias-correction trials. SEEFs are trials set up to determine the detection rate of ground surveyors, while CPTs involve the placement and regular checking of carcasses placed on the landscape to monitor rate of decay and removal by scavengers (USFWS 2012). The information gleaned from SEEFs and CPTs is used to inform the monitoring process and evaluate detection rates of carcasses by ground surveyors during actual standardized carcass searches, ultimately informing fatality estimates. While every effort is made to track wildlife collisions to the highest degree, biological monitoring at wind energy facilities is unfortunately not exempt from the same problems, such as time, cost, and data quality, as other methods of traditional wildlife monitoring (Gardner et al. 2008).

Due to this conundrum, there has been an increase in the use of uncrewed aircraft systems (UAS) to complete monitoring and research objectives because of their efficiency in data collection (Wargo et al. 2014). Uncrewed aerial systems can accomplish monitoring goals more efficiently than human surveyors, as they can cover difficult terrain quickly and generate near-real time data (Koh and Wich 2012). UAS have even been used to monitor recreational use of remote habitats and deploy park rangers to specific problem areas (Koh and Wich 2012). UAS also have successfully detected flora and fauna of all sizes, distinguished land use classifications, and estimated abundance, distribution, and habitat use (Chabot and Bird 2012, Koh and Wich 2012, Hodgson et al. 2016, 2018, Poysa et al. 2018). Further advances in this technology, such as the use of coordinated UAS teams, may increase the amount of ground that can be covered in an efficient manner without creating spatial and temporal data gaps (Floreano and Wood 2015). Moreover, this technology has been shown to outperform expertly trained ground and aerial human surveyors, all while only requiring minimal training to operate the technology itself (Koh and Wich 2012). Lastly, there is the added benefit of expanding beyond the environmental monitoring sphere with UAS technology and applying it to the inspection and maintenance of energy infrastructure (Floreano and Wood 2015). Despite this, there is some regulatory tape that can hinder work with Uncrewed Aerial Vehicles (UAVs). Qualified UAS pilots are typically required to remain on-site and within line-of-sight when operating UAS, and past work has primarily only utilized one UAS at a time (FAA 2016). This still requires the use of expert staff power and time-consuming surveying.

To meet these challenges, the technology startup Thread is working towards the development of advanced technologies to meet energy needs (Reidy 2019). Rather than employ expensive external vendors for both turbine maintenance and wildlife monitoring, which requires numerous employees exposed to risky environments to complete time costly tasks, Thread is proposing bringing these tasks in-house, equipping wind energy companies with one package to meet multiple purposes in a time efficient, low-cost manner. Multiple tasks can be completed by one technician with the accrual of a Federal Aviation Administration (FAA) waiver in 2020 to fly multiple UAS by a single operator. These UAS would be capable of doing multiple tasks (e.g., infrastructure and wildlife surveys) allowing companies to perform surveys remotely and with fewer staff, even alleviating safety concerns (e.g., technicians climbing wind turbines for inspections). Thread envisions the use of an onsite “nest” (i.e., housing that stores and charges UAS, as well as acts as the brain for uploading data and navigating survey schedules) at wind energy centers can allow UAS procedures to be implemented remotely and performed autonomously, saving environmental and energy companies both time and money when monitoring post-construction wind energy sites (Reidy 2019).

Prior work must be done to train the system to learn what it is being used to search for before reaching the point where UAS are operating effectively and efficiently in either environmental or infrastructure aspects. In the past, experts and citizen scientists have been used to manually count focal objects in imagery taken from cameras attached to UAS, which can be a very time-laborious activity and introduces another source of potential error in detection (Poysa et al. 2018). To solve this conundrum, a convolutional neural network (hereafter, “CNN”) is employed. The CNN is the processing brain behind accurate detections from UAS field collected imagery. Developing a CNN requires both time and expert knowledge in the field of computer science; however, the better prepared the CNN is, the more superior results that will be produced (Rosa et al. 2016). Many factors can play into the detection of a focal object, such as the surrounding land cover type, weather, sun angle, size, coloration, and the level of decay of a deceased animal (Linchant et al. 2015). As such, collecting UAS imagery in a variety of conditions can greatly improve the success of the CNN and resulting data (Linchant et al. 2015).

Objectives

In the following study, I aid in the development and evaluation of a multifaceted package to improve post-construction mortality monitoring of birds and bats, along with live breeding waterfowl monitoring that can be used in a variety of wildlife assessments and even basic research questions on mate choice and territoriality. To improve wildlife mortality monitoring at wind energy sites in both time, money, and data quality, I aim to develop and evaluate a CNN to ultimately pair with the Thread uncrewed aircraft system. In Chapter II, I develop and validate a convolutional neural network for the detection of bird and bat carcasses. In Chapter III, I explore the same dataset for its accuracy in species classification and factors impacting its success. In Chapter IV, I perform a proof-of-concept test, looking at a side-by-side comparison of the trained CNN against ground surveyors in a simulated post-construction monitoring scenario. In Chapter V, I compare counts of waterfowl on wetlands from manual review of RGB UAS imagery to current ground count approaches to support both pre-construction wind farm surveys and historic waterfowl surveys. In Chapter VI, I conclude with a summary of the previous chapters and recommendations for future research and applications.

Literature Cited

Bagstad, K. J., D. J. Semmens, J. E. Diffendorfer, B. J. Mattsson, J. Dubovsk, W. E. Thogmartin, R. Wiederholt, J. Loomis, J. A. Bieri, C. Sample, J. Goldstein, and L. Lopez-Hoffman. 2019. Ecosystem service flows from a migratory species: spatial subsidies of the northern pintail. Ambio 48:61–73.

Baltezore, J.F. and J.A. Leitch. 1992. Expenditures and economic impact of resident and nonresident hunters and anglers in North Dakota, 1990–91 season. Department of Agricultural Economics: Agricultural Economics Report No. 289.

Barrios, E., V. Valencia, M. Jonsson, A. Brauman, K. Hairiah, P. E. Mortimer, and S. Okubo. 2018. Contribution of trees to the conservation of biodiversity and ecosystem services in agricultural landscapes. International Journal of Biodiversity Science, Ecosystem Services & Management 14(1):1–16.

Belaire, J. A., L. M. Westphal, C. J. Whelan, and E. S. Minor. 2015. Urban residents' perceptions of birds in the neighborhood: biodiversity, cultural ecosystem services, and disservices. Condor 117(2):192–202.

Bumrunsgri, S., E. Sripaoraya, T. Chongsiri, K. Sridith, and P. A. Racey. 2009. The pollination ecology of durian (*Durio zibethinus*, Bombacaceae) in southern Thailand. Journal of Tropical Ecology 25:85.

Campbell-Lendrum, D. and C. Corvalan. 2007. Climate change and developing-country cities: implications for environmental health and equity. Journal of Urban Health: Bulletin of the New York Academy of Medicine 84(1): i109–i117.

Chabot D., and D.M. Bird. 2012. Evaluation of an off-the-shelf unmanned aircraft system for surveying flocks of geese. Waterbirds 35: 170–174.

Chan, M. 2009. Cutting carbon, improving health. The Lancelet 374:1870–1871.

Chretien, L. P., J. Theau, and P. Menard. 2015. Wildlife multispecies remote sensing using visible and thermal infrared imagery acquired from an unmanned aerial vehicle (UAV). International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XL-1/W4:241-248.

Clergeau, P., G. Mennechez, A. Sauvage, and A. Lemoine. 2001. Human perception and appreciation of birds: a motivation for wildlife conservation in urban environments of France. Pages 69–88 *in* Marzluff, J. M., R. Bowman, R. Donnelly, editors. Avian Ecology and Conservation in an Urbanizing World. Springer, Boston, MA, USA.

Coon, R., D. Bangsund, and N. Hodur. 2014. The economic base of North Dakota: a measure of the state's economy in 2012. North Dakota State University: AAE Staff Paper 14001.

Cordts, S. D., G. G. Zenner, and R. R. Koford. 2002. Comparison of helicopter and ground counts for waterfowl in Iowa. Wildlife Society Bulletin 30(2):317-326.

De Deyn, G. B., J. H. C. Cornelissen, and R. D. Bardgett. 2008. Plant functional traits and soil carbon sequestration in contrasting biomes. Ecology Letters 11:516–531.

Det Norske Veritas Germanischer Lloyd [DNV GL]. 2018. Energy transition outlook 2018: a global and regional forecast to 2050. Det Norske Veritas Germanischer Lloyd. 322 pp.

DeVault, T. L., O. E. Rhodes, Jr., and J. A. Shivik. 2003. Scavenging by vertebrates: behavioral, ecological, and evolutionary perspectives on an important energy transfer pathway in terrestrial ecosystems. Oikos 102:225–234.

Eggeman, D. R., and F. A. Johnson. 1989. Variation in effort and methodology for the midwinter waterfowl inventory in the Atlantic Flyway. Wildlife Society Bulletin 17:227–233.

Federal Aviation Administration [FAA]. 2016. Summary of small unmanned aircraft rule (part 107). FAA News, Federal Aviation Administration, Washington, D.C.

Fleming, P. J. S., and J. P. Tracey. 2008. Some human, aircraft and animal factors affecting aerial surveys: how to enumerate animals from the air. Wildlife Research 35:258-267.

Floreano, D. and R. Wood. 2015. Science, technology and the future of small autonomous drones. Nature 521(7553): 460–466.

Frick, W. F., J. F. Pollock, A. C. Hicks, K. E. Langwig, D. S. Reynolds, G. G. Turner, C. M. Butchkoski, and T. H. Kunz. 2010. An emerging disease causes regional population collapse of a common North American bat species. Science 329(5992):679-682.

Frick, W. F., E. F. Baerwald, J. F. Pollock, R. M. R. Barclay, J. A. Szymanski, T. J. Weller, A. L. Russell, S. C. Loeb, R. A. Medellin, and L. P. McGuire. 2017. Fatalities at wind turbines may threaten population viability of a migratory bat. Biological Conservation 209:172–177.

Gardner T., J. Barlow, I. Araujo, T. Ávila-Pires, A. Bonaldo, J. Costa, M. Esposito, F. Ferreira, J. Hawes, M. Hernandez, M. Hoogmoed, R. Leite, N. Lo-Man Hung, J. Malcolm, M. Martins, L. Mestre, R. Miranda-Santos, W. Overal, L. Parry, S. Peters, M. Ribeiro, M. Da Silva, C. Da Silva Motta, and C. Peres. 2008. The cost-effectiveness of biodiversity surveys in tropical forests. Ecology Letters 11(2): 139–150.

Gibbs, J. P., H. L. Snell, and C. E. Causton. 1999. Effective monitoring for adaptive wildlife management: lessons from the Galapagos Islands. Journal of Wildlife Management 63(4):1055–1065.

Grado, S. C., K. M. Hunt, C. P. Hutt, X. T. Santos, and R. M. Kaminski. 2011. Economic impacts of waterfowl hunting in Mississippi derived from a state-based mail survey. Human Dimensions of Wildlife 16:100–113.

Green, A. J., and J. Elmberg. 2014. Ecosystem services provided by waterbirds. Biological Reviews 89:105–122.

Habib, T. J., D. A. Moore, and E. H. Merrill. 2012. Detection and stratification approaches for aerial surveys of deer in prairie-parklands. Wildlife Research 39(7):593–602.

Heusmann, H. W. 1999. Let's get rid of the Midwinter Waterfowl Inventory in the Atlantic Flyway. Wildlife Society Bulletin 27(3):559–565.

Hiraldo, F., J. C. Blanco, and J. Bustamante. 1991. Unspecialized exploitation of small carcasses by birds. Bird Study 38(3):200-207.

Hodgson, J., S. Baylis, R. Mott, A. Herrod, and R. Clarke. 2016. Precision wildlife monitoring using unmanned aerial vehicles. Scientific Reports 6(22574).

Hodgson, J., R. Mott, S. Baylis, T. Pham, S. Wotherspoon, A. Kilpatrick, R.R. Segaran, I. Reid, A. Terauds, and L. Koh. 2018. Drones count wildlife more accurately and precisely than humans. Methods in Ecology and Evolution 9(5): 1160–1167.

Hoffmaster, E., J. Vonk, and R. Mies. 2016. Education to action: improving public perception of bats. Animals 6(6):1–9.

Johnson, W. C., B. V. Millett, T. Gilmanov, R. A. Voldseth, G. R. Guntenspergen, and D. E. Naugle. 2005. Vulnerability of northern prairie wetlands to climate change. BioScience 55(10):863-872.

Jones, G., L. Pearlstine, and H. Percival. 2006. An assessment of small unmanned aerial vehicles for wildlife research. Wildlife Society Bulletin 34(3):750–758.

Katzner, T., V. Bennett, T. Miller, A. Duerr, M. Braham, and A. Hale. 2016. Wind energy development: methods for assessing risks to birds and bats pre-construction. Human-Wildlife Interactions 10(1):42-52.

Kingsford, R. T., and J. L. Porter. 2009. Monitoring waterbird populations with aerial surveys-what have we learnt? Wildlife Research 36:29–40.

Koh, L. and S. Wich. 2012. Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. Tropical Conservation Science 5(2): 121–132.

Kuvlesky, W., L. Brennan, M. Morrison, K. Boydston, B. Ballard, and F. Bryant. 2007. Wind energy development and wildlife conservation: challenges and opportunities. Journal of Wildlife Management 71(8): 2487–2498.

Kiesecker, J., J. Evans, J. Fargione, K. Doherty, K. Foresman, T. Kunz, D. Naugle, N. Nibblelink, and N. Niemuth. 2011. Win-win for wind and wildlife: a vision to facilitate sustainable development. PLoS ONE 6(4).

Linchant, J., J. Lisein, J. Semeki, P. Lejeune, and C. Vermeulen. 2015. Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. Mammal Review 45(4): 239–252.

Maas, B., D. S. Karp, S. Bumrungsri, K. Darras, D. Gonthier, J. C. -C. Huang, C. A. Lindell, J. J. Maine, L. Mestre, N. L. Michel, E. B. Morrison, I. Perfecto, S. M. Philpott, C. H. Sekercioglu, R. M. Silva, P. J. Taylor, T. Tscharntke, S. A. Van Bael, C. J. Whelan, and K. Williams-Guillen. 2016. Bird and bat predation services in tropical forests and agroforestry landscapes. Biological Reviews 91:1081–1011.

Mahlum, B.J. and N. Perez. 2012. U.S. Fish and Wildlife Service, Ducks Unlimited focus funding to protect vital waterfowl habitat in the Prairie Pothole Region. U.S. Fish and

Wildlife Service <https://www.fws.gov/midwest/news/512.html>. Accessed Feb. 12, 2020.

< https://gf.nd.gov/wildlife/habitats/tallgrass>.

Ndembe, E., D.A. Bangsund, and N.M. Hodur. 2019. Resident and nonresident hunter and angler expenditures, characteristics, and economic effects, North Dakota, 2017–2018. North Dakota State University: Agribusiness and Applied Economics Report 785.

Ogden, L. E. 2013. Drone ecology. BioScience 63(9): 776.

Peters, K. and C. Farmer. 2018. Foxtail Wind Energy Center Wildlife Conservation Strategy. DNV GL. 116 pp.

Poysa, H., J. Kotilainen, V. Vaananen, and M. Kunnasranta. 2018. Estimating production in ducks: a comparison between ground surveys and unmanned aircraft surveys. European Journal of Wildlife Research 64(74).

Ransom, J. I. 2012. Detection probability in aerial surveys of feral horses. Journal of Wildlife Management 76(2):299-307.

Reidy, J. 2019. Application for the onsite installation of secure, remote, autonomous, multi-drone operations within the North Dakota Renewable Energy Sector. North Dakota Industrial Sector Renewable Energy Program. 40 pp.

Ringold, P. L., J. Alegria, R. L. Czaplewski, B. S. Mulder, T. Tolle, and K. Burnett. 1996. Adaptive monitoring design for ecosystem management. Ecological Applications 6(3):745–747.

Rodhouse, T. J., R. M. Rodriguez, K. M. Banner, P. C. Ormsbee, J. Barnett, and K. M. Irvine. 2019. Evidence of region-wide bat population decline from long-term monitoring and

Bayesian occupancy models with empirically informed priors. Ecology and Evolution 9:11078-11088.

Rosa, I.M.D., A.T. Marques, G. Palminha, H. Costa, M. Mascarenhas, C. Fonseca, and J. Bernardino. 2016. Classification success of six machine learning algorithms in radar ornithology. Ibis 158: 28–42.

Rosenberg, K. V., A. M. Dokter, P. J. Blancher, J. R. Sauer, A. C. Smith, P. A. Smith, J. C. Stanton, A. Panjabi, L. Helft, M. Parr, and P. P. Marra. 2019. Decline of the North American avifauna. Science 366:120-124.

Shaffer, J. and D. Buhl. 2016. Effects of wind-energy facilities on breeding grassland bird distributions. Conservation Biology 30(1): 59–71.

Smith, G. W. 1995. A critical review of the aerial and ground surveys of breeding waterfowl in North America. National Biological Service. Biological Scientific Report 5, Washington, D. C.

U.S. Fish and Wildlife Service [USFWS]. 2012. U.S. Fish and Wildlife Service land-based wind energy guidelines. U.S. Fish and Wildlife Service, Washington, D.C. 82 pp.

Veers P., K. Dykes, E. Lantz, S. Barth, C. Bottasso, O. Carlson, A. Clifton, J. Green, P. Green, H. Holttine, D. Laird, V. Lehtomäk, J. Lundquist, J. Manwell, M. Marquis, C. Meneveau, P. Moriarty, X. Munduate, M. Muskulus, J. Naughton, L. Pao, J. Paquette, J. Peinke, A. Robertson, J. Rodrigo, A. Sempreviva, J. Smith, A. Tuohy, and R. Wiser. 2019. Grand challenges in the science of wind energy. Science 366.

Wanger, T. C., K. Darras, S. Bumrungsri, T. Tscharntke, and A. M. Klein. 2014. Bat pest control contributes to food security in Thailand. Biological Conservation 171:220–223.

Wargo, C.A., G.C. Church, J. Glaneueski, and M. Strout. 2014. Unmanned aircraft systems (UAS) research and future analysis. 2014 IEEE Aerospace Conference, Big Sky, MT. 16 pp.

Wenny, D. G., T. L. DeVault, M. D. Johnson, D. Kelly, C. H. Sekercioglu, D. F. Tomback, and C. J. Whelan. 2011. The need to quantify ecosystem services provided by birds. Auk 128(1):1–14.

Whelan, C. J., D. G. Wenny, and R. J. Marquis. 2008. Ecosystem services provided by birds. Annuals of the New York Academy of Sciences 1134:25–60.

Whelan, C. J., C. H. Sekercioglu, and D. G. Wenny. 2015. Why birds matter: from economic ornithology to ecosystem services. Journal of Ornithology 156:S227–238.

CHAPTER II DEVELOPING AND EVALUATING A CONVOLUTIONAL NEURAL NETWORK TO ASSESS REMOTELY SENSED IMAGERY FOR BIRD AND BAT MORTALITY MONITORING AT WIND ENERGY FACILITIES

Abstract

1. Post-construction mortality monitoring of birds and bats at wind energy sites is vital to the sustainable future of renewable energy and conservation; however, traditional methods are prone to low detection rates and broad confidence intervals, leading to wide uncertainty in fatality estimates used for regulatory compliance, siting, and conservation efforts.
2. Uncrewed aerial systems (UAS) and machine learning are increasingly incorporated in wildlife conservation work due to high precision, repeatability, low risk, and commercial availability. We developed two different convolutional neural networks (CNN) to detect avian and bat mortalities at wind energy sites from UAS imagery taken both on-site at a wind energy facility and off-site in changing seasonal background covers (i.e., brown, green) to aid in generalization. Secondly, we planned to use generalized linear models to relate binary detection to environmental and computational variables that best explain identification in the developed neural network model.
3. Accuracy across all models was 98.7%. The algorithms performed so well there was virtually no variability in model detection, and as such, we were unable to model the predictors and present summary statistics instead.
4. *Synthesis and applications:* In this paper, we showed that pairing a convolutional neural network with UAS led to high detection rates for birds and bats in a post-construction mortality monitoring scenario. The increased detection rates from reported detection rates of current methodology should lead to more precise fatality estimates to better inform

siting, mitigation, and conservation efforts. This technique may be applied to a variety of scenarios and sectors, including but not limited to transportation, energy, public health, defense, and conservation. Integrating technology with real-world problems has the potential to change multiple sectors actively working towards a more sustainable future.

Keywords detection, machine learning, monitoring, mortality monitoring, neural network, searcher efficiency, uncrewed aerial system, wind energy

Introduction

Heightening concerns over anthropogenic-driven climate change have initiated an urgent worldwide call to lower global temperature (Horowitz, 2016; Hoegh-Guldberg et al., 2019; IPCC, 2021). This push towards reduced emissions has been particularly evident within the energy sector, where calls for fossil fuel reductions to minimize carbon dioxide emissions have spurred the renewable energy movement (Mathews, 2014). While there has been a suite of renewable energy solutions developed, including solar, geothermal, and wave power, wind energy has emerged as a leader. Within a short time, wind energy has been implemented at a broad-scale and is expected to increase by ten times prior to the year 2050 (DNV GL, 2018; Veers et al., 2019). Current global annual investment in wind energy is $100 billion (US), and it will soon become one of the world's big energy sources (DNV GL, 2018; Veers et al., 2019). Wind energy is appealing due to it being broadly available, renewable, low cost, and having minimal pollution output (Veers et al., 2019), ultimately offering both public and environmental health benefits of cleaner air (Campbell-Lendrum & Corvalan, 2007; Chan, 2009).

However, wind energy can also have negative impacts to the surrounding environment, particularly on wildlife such as birds and bats, through direct mortalities, habitat fragmentation, and displacement (Kuvlesky et al., 2007; Kiesecker et al., 2011; Shaffer & Buhl, 2015).

Monitoring of bird and bat populations is proving to be increasingly important as long-term drastic declines have been documented due to habitat loss and degradation, fragmentation, disease, environmental contaminants, and collisions with anthropogenic development like buildings and wind turbines (Rosenburg et al., 2019; USFWS, 2021). Since the 1950s, birds have experienced a 50% decline (Rosenburg et al., 2019), meanwhile regional estimates of bat populations have shown reductions of 75% within a two-year span due to white-nosed syndrome alone (Blehert et al., 2009). Specific to wind energy-related mortalities, an estimated 600,000 – 888,000 bats and 234,000 – 573,000 birds were killed in 2012 (Hayes, 2013; Loss et al., 2013; Smallwood, 2013; Smallwood & Bell, 2020). With rapid expansions of wind energy within major flight corridors such as the Prairie Pothole Region of North Dakota, a vital area to breeding birds (Batt et al., 1989; USFWS, 2008), reliable, high-quality monitoring of bird and bat species is necessary for science-based decision-making conservation efforts (Nichols & Williams, 2006).

In the wind energy sector, bird and bat fatality impacts are estimated through post-construction mortality monitoring (hereafter, PCMM) required by the Endangered Species Act, Migratory Bird Treaty Act, National Environmental Policy Act, and the Bald and Golden Eagle Act (USFWS, 2012). For at least one year following construction of newly erected wind farms, PCMM ground search surveys typically include standardized carcass searches, searcher efficiency trials (hereafter, SEEFs), and carcass persistence trials (hereafter, CPTs) (USFWS, 2012). While standardized carcass searches throughout this time provide mortality data, SEEFs and CPTs are bias-correction trials. SEEFs are trials designed to determine the detection rate of ground surveyors, while CPTs involve the placement and regular checking of carcasses placed on the landscape to monitor rate of decay and removal by scavengers (USFWS, 2012). The information gleaned from SEEFs and CPTs is then used to inform the monitoring process and evaluate detection rates of carcasses by ground surveyors during actual standardized carcass searches. While every effort is made to track wildlife collisions to the highest degree, biological monitoring at wind energy facilities is prone to the same issues as common traditional monitoring techniques, such as time, cost, staff power, and data quality (Gardner et al., 2008). Human surveyors have an average searcher efficiency rate of 65% but range as low as 5 – 23% depending on size and condition of carcass remains (Reyes et al., 2016; Barrientos et al., 2018). When paired with canine detection dogs, searcher efficiency increases to 87%, but ranges 69 – 100% (Barrientos et al., 2018). Further, traditional ground searches can also lead to 44% misidentified species and error in time since death estimations (Smallwood, 2018). Imperfect detection rates can result in broad confidence intervals surrounding mortality estimates and subsequently impact population models on levels of impact and decision making (Guillera-Arroita et al., 2014). Further, ground surveys conducted on foot by researchers can be negatively impacted due to inconsistent surveying strategies and survey areas, and coverage restrictions due to time and money (Eggeman & Johnson, 1989; Smith, 1995; Heusmann, 1999; Kingsford & Porter, 2009). When coupled with observer bias and counting error, there is a need for other methodological approaches that achieve improved estimation for extrapolating fatality estimates at wind energy sites.

Many sectors are turning to uncrewed aerial systems (hereafter, UAS) to complete monitoring and research objectives due to their efficiency in data collection (Wargo et al., 2014). UAS can accomplish monitoring goals more effectively than human surveyors, as they can cover difficult terrain quickly and generate repeatable, near-real time data (Koh & Wich 2012). However, experts and citizen scientists have typically been used in post-processing to manually count focal objects in the UAS imagery, which can be a very time-laborious activity and introduces another source of potential error in detection (Poysa et al., 2018). To solve this conundrum, a convolutional neural network (hereafter, CNN) is employed. The CNN is a deep machine learning classifier that can detect and localize targets in imagery. Developing a CNN requires both time and expert knowledge in the field of computer science; however, the better trained the CNN is, the better the results (Rosa et al., 2016). Many factors can play into the detection of a focal object, such as the surrounding land cover type, weather, sun angle, size, coloration, and the level of decay of a deceased animal (Linchant et al., 2015). As such, collecting UAS imagery in a variety of conditions can greatly improve the success of the CNN and resulting data (Linchant et al., 2015). Pairing a trained CNN with an UAS to detect and localize bird and bat mortalities during PCMM work at wind energy sites has the potential to lead to increased quality and quantity of data, ultimately increasing synergy between the wind energy and conservation sectors for scientifically sound sustainability measures.

The objective of our work was to develop and evaluate a CNN that uses imagery collected from UAS to conduct mortality monitoring surveys for wind energy. We hypothesize that while we expect overall detection rates to be higher from the trained CNN than previously reported averages for humans and canines, we also anticipate that sun angle, wind, sky cover, ground cover, and size of target will negatively impact the detection of carcasses in a trained CNN. More specifically, we anticipate that a low sun angle will cause increased shadowing (Zhou et al. 2021), that a clear sky will increase reflectance and washout defining color characteristics on targets, and higher wind speeds will create more image blur, all likely causing reduced detection. Furthermore, we expect that vegetation will obscure carcasses, and that smaller carcasses such as songbirds and bats will be less likely to be detected than targets within typically larger species groups (i.e., waterfowl, raptors, waterbirds, gulls/terns, and upland gamebirds). Additionally, we hypothesize that carcasses that fall on image edges will likely have reduced detection due to partial carcass availability and as such, limited degree of image context (Reina et al., 2020). From this, we hope to not only inform those planning to build a CNN for wildlife detection where potential weak spots may lie, but also explain PCMM detection probabilities for improved bird and bat fatality metrics.

Materials and Methods

Study Area

We used two sites to collect imagery for training and testing our CNNs. The first site served as an actual wind site with current PCMM occurring, while the second provided opportunities for additional data collection in different background covers and establish simulated plots for image collection and testing.

Wind Energy Center– The wind energy center (hereafter, WEC) is located in Dickey County, North Dakota on the Missouri Coteau (Fig. 1) placing it within the Prairie Pothole Region (hereafter PPR; USFWS, 2008). The PPR comprises a vast section of formerly glaciated terrain now covered in wetlands that produce most of North America's waterfowl populations (Batt et al., 1989; USFWS, 2008). Within the PPR, the WEC covers 8,105.6 ha predominantly covered in grasslands (60.6%), pasture (12.1%), crops (8.9%), scrub-shrub (8.6%), and open water (6.6%), with developed open space, emergent herbaceous wetlands, deciduous forest, woody wetlands, and barren land totaling the remaining 3.2% (Homer et al., 2015). There are 75 total turbines mounted on a tubular tower to minimize perching opportunities for raptors. The energy company randomly selected five of these turbines for an environmental consulting company (hereafter, ECC) to perform cleared plot surveys for post-construction mortality monitoring efforts. Cleared plots are defined as landowner maintenance of no to minimal vegetation within a 14,400 m^2 (120 m x 120 m) area around each of the five turbines to improve ground surveyor visibility (Peters & Farmer, 2018).

Grand Forks County, ND– Grand Forks County is in the Red River Valley, a low-lying tallgrass prairie in the eastern part of the state (Fig. 1). Formerly part of the Glacial Lake Agassiz, the landscape is flat with rich, saline soils that mostly provide for highly productive crop farming (NDGF, 2020). Study area lands encompassed 436.88 ha with 409.77 ha (93.8%) covered in cropland including soybeans, wheat, corn, and tilled soil, and 27.11 ha (6.2%) covered in pasture. We chose properties based on access, similarity to ground cover types available in the region and diversity in land cover type to aid in generalizing the convolution neural network model.

Field Methods

Standardized Carcass Search Field Methods– ECC ground surveyors implemented standardized carcass searches on a weekly basis between 15 March – 15 November 2020 to collect wildlife mortality data at the WEC following USFWS (2012) guidelines. A single ECC ground surveyor performed 6 m linear transects in cleared plots and slowly drove roads and pads within 100 m of all remaining turbines scanning for bird and bat mortalities. Carcass locations and species were reported weekly to be paired with UAS surveys.

We performed preprogrammed (DJI Ground Station Pro version 2.0) UAS lawnmower grid surveys at the cleared plots within 24–48 hours prior to ECC ground surveys to maximize opportunity for collecting imagery of detected mortalities within time constraints and prior to ECC removal. Surveys were performed weekly between 15 March – 15 November 2020. Using a quadcopter DJI Matrice 210 v2 RTK (color: black, weight: 4.8kg, operating temp: -20°C to

50°C) with a DJI Zenmuse X5S camera (RGB) sensor, we flew surveys at 9.14 m above ground at 1.8 m/s with 50% overlap. We chose the flight height to keep surveys in a safe flight zone below the rotor swept area of the moving wind turbine. We collected environmental data for each survey, including: time the survey started and stopped, temperature (°C), wind speed (mph) and direction, sky cover (NABBS, 2020), and turbine identification number, longitude and latitude at each captured image location, and flight height (m).

Off-site Training Data Collection Field Methods– From 15 March – 08 December 2020, we flew preprogrammed (DJI Ground Station Pro version 2.0) UAS surveys in Grand Forks to collect species and landcover imagery approximately twice monthly using the DJI Matrice 210 v2 RTK (color: black, weight: 4.8kg, operating temp: -20°C to 50°C). To mimic a standardized carcass search flight and maintain consistent imagery parameters, we flew surveys at 9.14 m above ground at 1.8 m/s with 50% overlap using a DJI Zenmuse X5S camera (RGB) to capture imagery in a lawnmower grid fashion.

We flew UAS surveys in 120 x 120 m plots in a variety of cover types, including: pasture, gravel roads, plowed dirt fields, and crop fields (corn, wheat, and soy). We used donated bird and bat carcasses that encompassed 56 species (51 bird species and 5 bat species) local to North Dakota. We distributed approximately 10 – 30 carcasses out in each plot on the landscape. We attempted to routinely rotate flight times between each survey day when weather and other logistics allowed. We also performed targeted imagery flights in which we manually flew the UAS over known-location bird and bat carcasses in a lawn-mower grid fashion to increase training data for CNN development.

Convolutional Neural Network Development

We created a labeled image library for building the neural network by pairing UAS imagery with environmental data collected at the WEC and Grand Forks. Biological experts from the University of North Dakota reviewed collected imagery and created boxes within a custom software application (Fig. 2) over known-location carcasses with associated labels related to species, sex, and carcass condition (i.e., intact, scavenged, dismembered, feather spot), and paired it with data including: season, time of day, latitude and longitude, derived sun angle (Cornwall et al., 2020), sky cover (NABBS, 2020), and surrounding ground cover within 5 m of the carcass. We then used this labeled image library to train the CNN.

We used a RetinaNet (Lin et al., 2017) object detection CNN model for the detection task which utilizes a ResNet (He et al., 2016) CNN as a backbone structure. We trained two models, one for each background color: Brown (dirt/gravel, spring and fall vegetation) and Green (summer vegetation). We used a roughly 80% training/20% validation image split. Splits were done by utilizing a randomized method which repeatedly attempted to assign images to the training and validation SEEFs such that the number of target examples for each class had an 80%/20% split. We used this method as this task is not trivial when an image can have multiple bounding boxes of different types within them, and in many cases, it is not possible to get perfect training/validation splits across all classes. We split 1,634 source brown background images into 1,312 training images and 322 validation images, and split 173 source green background images into 127 training images and 36 validation images.

Training the RetinaNet used a custom training pipeline developed by Thread, which generates training samples for each epoch of training the CNN by randomly selecting windows around bounding boxes in the training imagery. After that, the training images are passed through a series of data augmentations from the open source Albumentations library (Buslaev et al., 2018). For this work, we used the window size 400 x 400, followed by the RandomBrightnessContrast (50% application, brightness and contrast limits of 0.2) and Perspective (100% application, scale minimum and maximum values of 0.05 and 1.0) transforms. Because of these random data augmentations, images fed to the network during training were always different modified sub-windows of the training images. Validation and inference were performed by striding the trained RetinaNet over 400x400 windows (with a user-specified overlap, in this case 20 pixels) in the target images and then merging the predicted bounding boxes if class types were the same and the bounding boxes overlapped by at least 50%.

Environmental Factor Statistical Analysis

We modeled the factors impacting the detection capabilities of the trained neural network from UAS imagery collected at the WEC and Grand Forks. We included classified imagery from each of the two models, with 302 images from the brown model and four from the green model. Due to brown vegetative cover persisting on the landscape much longer than green in North Dakota, the majority (73.4%) of images taken for the green model were held back as training material. Due to this limitation, we combined results from both models. We considered a carcass detected if the CNN's confidence output was $\geq$80% and considered it not detected if it was < 80%. We had originally planned to relate detection (1) and non-detection (0) to wind speed (mph), sky cover (NABBS, 2020), carcass size (i.e., large bird, small bird, bat), sun angle derived from location and time data (Cornwall et al., 2020), if a carcass fell on a tile line (1) or not (0), and if a carcass fell on the edge of an image (1) or not (0) using a generalized linear model with a binomial distribution; however, detection from the CNNs was so high we ultimately lacked enough variability to perform the model. As a result, we instead present summary statistics. We did not incorporate accuracy of species assessment in this analysis, instead focusing solely on how well the model could find a carcass.

Results

We analyzed a total of 306 labeled carcasses in imagery to determine the variables that explain bird and bat mortality detection best using a convolutional neural network. Overall, the CNN had 302 carcass detections yielding an overall detection rate of 98.69%, with four missed detections. It should be noted that two of the four missed detections were detected, but the CNN's confidence fell below the 80% threshold at 72.34% and 36.03%. As such, we were unable to model any of the predictors as planned due to a lack of variability in the response and present summary statistics.

Despite the success in detection, the CNN counted a total of 536 false positives. The most common causes for false positives were humans (35.07%), shadows (13.06%), snow (12.5%), and vegetation (8.58%) (Appendix A). The average confidence output of false positives was 90.13% (range: 78.21 – 99.99%).

Discussion

The pairing of commercially available UAS with a trained CNN to detect and ultimately estimate bird and bat fatalities at wind energy sites has the potential to be transformative for both industry and conservation sectors. Recent studies show that human ground surveyors have average detection rates of 21.5 – 65% and canine surveyors of 77.3 – 87% (Barrientos et al., 2018; Domíniguez del Valle et al., 2020), with human surveyor searcher efficiency being negatively impacted by both carcass size and ground cover (Domíniguez del Valle et al. 2020).

With drastic documented population declines in both bird and bat species (Rodhouse et al., 2019; Rosenberg et al., 2019), increased precision in fatality estimates alongside projected wind energy growth may aid in future siting and mitigation efforts at renewable energy sites and help inform regional and national conservation efforts. Our research indicates that the pairing of UAS and a trained CNN have a higher average detection rate than other commonly used PCMM survey methods. For species that may be rare and small in size, the ability to increase confidence in fatality estimates may greatly impact mitigation needs at sites. For example, if a surveying method yields only a 10% detection rate, then it is difficult to discern if a species was present but went undetected compared to if the surveying method has an 80% detection rate where a non-detection of the species would be more likely to be an absence than just a missed observation. Therefore, increased detection rates lead to narrower confidence intervals and higher precision in fatality estimation (Rabie et al., 2021), which could translate into less area or fewer turbines that need to be searched ultimately increasing efficiency, saving time, effort, and cost. It may also lead to reduced mitigation efforts overall for instances when species of concern may not actually be impacted by the wind turbines.

However, using this approach requires an understanding of its applicability and efficacy in particular scenarios. While our dataset did not provide any variability specific to binary detection, more attention may be needed to predict and account for areas of weakness regarding false positives. Similar to the use of UAS, wind speed must be considered when applying this method, as image blur and aircraft unsteadiness coupled with vegetation movement may create more room for false positive errors. Further, increased variation and complexity in training datasets is likely to aid in generalization and further reduction of false positives of CNN models. Additionally, while we were unable to model detection relative to cover type, operators should consider the vegetation structure and growth stage being surveyed as certain crops may be better suited to this method than others. For example, cereal grains may obscure carcasses less than mature soybeans and corn that have a wider, more complex canopy, but further research is required to explore this possibility and establish best practices.

Our study presented several limitations, including an unbalanced dataset with samples from the brown model heavily outweighing samples from the green model. This was largely due to a limited growing season in North Dakota, coupled with a post-data collection decision to develop more than one CNN model to match cover background for improving detection. It is possible that we would see more variability in our binary detection results had we been able to test more samples from the green model, as vegetative cover during the growing season and reflectance may influence detection success. Future researchers should be careful when considering modeling approaches for neural networks prior to data collection, being more specific when considering study design and generalizing from there as needed, rather than the reverse. Further, we experienced almost twice as many false positives in our dataset than we did true positives due to non-target detections most commonly of humans, shadows, snow, and vegetation. The complexity in wildlife and environmental imagery can create a number of causes for false positives, which can be combatted in several ways. Increasing the complexity of training datasets and annotating non-target objects may lead to a better-informed model with fewer false positives. However, we recognize this takes an extensive amount of time, and as such we recommend determining common false positives in the initial dataset prior to annotating non-target objects to better allocate efforts. Additionally, particularly in datasets with high confidence in true positive detections, confidence thresholds can be fine-tuned to weed out the majority of false positives. While this would typically be performed using receiver operating characteristic (ROC) curves to visualize sensitivity versus specificity across confidence thresholds, our data does not specifically look at the occurrence of true negatives, which is integral to calculating specificity. While there are large amounts of dead space in environmental imagery with the absence of targets, further exploration of this may be possible if an area within an image, or by individual image, is pre-defined as what can constitute a true negative. To attempt to address this, we viewed areas of non- or minimal amounts of overlap between confidence estimates and standard deviations associated with true positive and false positive detections. The average confidence estimate for a true positive was 99.4% +/- 2.2, whereas the average confidence estimate for a false positive was 90.2% +/- 5.7. Using the range of non-overlap, the ideal confidence threshold for this dataset to reduce the occurrence of false positives falls between 95.9 and 97.2% (Figure 3). Last, the likelihood of humans being in imagery taken for post-construction monitoring is low, and can be further reduced simply by ensuring that the UAS pilot and other technicians in the area are located outside of the search area while collecting imagery, which would have reduced the occurrence of false positives in our dataset greatly.

While this integrated technology indicates large strides towards increasing precision in wildlife conservation and efficiency for industry compliance, further validation is needed to compare searcher method efficacy between traditional survey methods and this burgeoning technology incorporating indirectly accounted factors such as vegetation height and density. Further, given the number of potential images that could be collected at a single wind farm if surveying all turbines, biologists must consider the ability to process the imagery rapidly so that carcasses can be removed soon after discovery to prevent scavenger removal and attraction within the rotor-swept area. Current solutions are to have onboard processing, a series of local graphics processing units, or cloud-based options. However, cloud-based processing can have long upload times in rural locations where wind sites are often located, but quick image classification, and as such may require infrastructure upgrades at wind sites. Despite this, initial efforts with this integrated technology are promising and further collaboration among industry, conservation, and the software engineering sectors may hold the key to efficiency that will facilitate higher quality data for understanding wildlife impact studies. Such approaches could be applied to a variety of other complicated human-wildlife interfaces, including but not limited to solar facilities, wildlife-vehicle collisions, airport runway safety (Zhou et al. 2021), railroad mortalities (Dasoler et al. 2020), zoonotic disease outbreaks, or oil spill cleanup and monitoring efforts.

Acknowledgments

The authors are extremely grateful to funding sources from the North Dakota Department of Commerce (Award: 19-11-G-229), University of North Dakota, Microsoft AI for Earth Grant (Award: MS-AZR-0036P), and the AmericaView North Dakota View Scholarship (USGS grant G18AP00077). We are very thankful for our partnerships and input from Xcel Energy, North Dakota Department of Game and Fish, and the U.S. Fish and Wildlife Service.

Literature Cited

Barrientos, R., Martins, R. C., Ascensão, F., D'Amico, M., Moreira, F., & Borda-de-Àgua, L. (2018). A review of searcher efficiency and carcass persistence in infrastructure-driven mortality assessment studies. *Biological Conservation 222*:146-153. https://doi.org/10.1016/j.biocon.2018.04.014.

Batt, B. D. J., Anderson, M. G., Anderson, C. D., & Caswell, F.D. (1989). Use of prairie potholes by North American ducks. In A. Van der Valk (Eds.), *Northern Prairie Wetlands* (pp.204-227). Iowa State University, Ames, USA.

Blehert, D. S., Hicks, A. C., Behr, M., Meteyer, C. U., Berlowski-Zier, B. M., Buckles, E. L., Coleman, J. T. H., Darling, S. R., Gargas, A., Niver, R., Okoniewski, J. C., Rudd, R. J., & Stone, W. B. (2008). Bat white-nose syndrome: an emerging fungal pathogen? *Science 323(5911)*: 227. https://doi.org/10.1126/science.1163874

Burnham, K. P., & Anderson, D. R. (2002). Model selection and multi-model inference. Second edition. Berlin, Germany: Springer.

Buslaev, A., V. I. Iglovikov, E. Khvedchenya, A. Parinov, M. Druzhinin, & A. A. Kalinin. (2020). Albumentations: fast and flexible image augmentations. *Information 11(2):125.* https://doi.org/10.3390/info11020125

Campbell-Lendrum, D. & Corvalan, C. (2007). Climate change and developing-country cities: implications for environmental health and equity. *Journal of Urban Health: Bulletin of the New York Academy of Medicine 84(1)*, i109–i117, https://doi.org/10.1007/s11524-007-9170-x

Chan, M. (2009). Cutting carbon, improving health. *The Lancet 374(9705)*, 1870-1871. https://doi.org/10.1016/S0140-6736(09)61993-0

Cornwall, C., A. Horiuchi, and C. Lehman. (2020). Solar position calculator. Boulder, CO, USA: National Oceanic and Atmospheric Administration: Earth Systems Research Lab. <https://esrl.noaa.gov/gmd/grad/solcalc/>.

Dardis, C. (2015). LogisticDx: diagnostic tests for models with a binomial response. R package version 0.2. <https://CRAN.R-project.org/package=LogisticDx>.

Det Norske Veritas Germanischer Lloyd [DNV GL]. (2018). Energy transition outlook 2018: a global and regional forecast to 2050. *Det Norske Veritas Germanischer Lloyd*. 322 pp.

Gardner T., Barlow, J., Araujo, I., Ávila-Pires, T., Bonaldo, A., Costa, J., Esposito, M., Ferreira, F., Hawes, J., Hernandez, M., Hoogmoed, M., Leite, R., Lo-Man Hung, N., Malcolm, J., Martins, M., Mestre, L., Miranda-Santos, R., Overal, W., Parry, L., Peters, S., Ribeiro, M., Da Silva, M., Da Silva Motta, C., & Peres, C. (2008). The cost-effectiveness of biodiversity surveys in tropical forests. *Ecology Letters 11(2)*: 139–150. https://doi.org/10.1111/j.1461-0248.2007.01133.x

Dasoler, B. T., Kindel, A., Beduschi, J., Biasotto, L. D., Dornas, R. A. P., Gonçalves, L. O., Lombardi, P. M., Menger, T., Schuck de Oliveira, G., & Teixeira, F. Z. (2020). The need to consider searcher efficiency and carcass persistence in railway wildlife fatality studies. *European Journal of Wildlife Research 66(81)*. https://doi.org/10.1007/s10344-020-01417-7.

Domíniguez del Valle, J., Peralta, F. C., & Arjona, M. I. A. (2020). Factors affecting carcass detection at wind farms using dogs and human searchers. *Journal of Applied Ecology(57):* 1926-1935. https://doi.org/10.1111/1365-2664.13714.

Eggeman, D. R. & Johnson, F.A. (1989). Variation in effort and methodology for the Midwinter Waterfowl Inventory in the Atlantic Flyway. *Wildlife Society Bulletin (1973-2006) 17(3)*: 227-233.

Gneiting, T. and Vogel, P. (2018). Receiver operating characteristic (ROC) curves. *arXiv preprint arXiv:1809.04808*.

Guillera-Arroita, G., Lahoz-Monfort, J. J., MacKenzie, D. I., Wintle, B. A., & McCarthy, M. A. (2014). Ignoring imperfect detection in biological surveys is dangerous: a response to 'fitting and interpreting occupancy models'. *PLoS ONE 9(7):* e99571. https://doi.org/10.1371/journal.pone.0099571.

Hayes, M. A. (2013). Bats killed in large numbers at United States wind energy facilities. *BioScience 63(12)*: 975-979. https://doi.org/10.1525/bio.2013.63.12.10

He, K., X. Zhang, S. Ren, and J. Sun. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition: 770-778.*

Heusmann, H. W. (1999). Let's get rid of the Midwinter Waterfowl Inventory in the Atlantic Flyway. *Wildlife Society Bulletin (1973-2006) 27(3)*:559-565. https://doi.org/10.3996/042017-JFWM-033

Hoegh-Guldberg, O., Jacob, D., Taylor, M., Guillén Bolaños, T., Bindi, M., Brown, S., Camilloni, I. A., Diedhiou, A., Djalante, R., Ebi, K., Engelbrecht, F., Guiot, J., Hijioka, Y., Mehrotra, S., Hope, C. W., Payne, A. J., Pörtner, H.-O., Seneviratne, S. I., Thomas, A., Warren, R., and G. Zhou. (2019). The human imperative of stabilizing global climate change at 1.5°C. *Science, 365*, 1263. https://doi.org/10.1126/science.aaw6974

Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N., Wickham, J., & Megown, K. (2015). Completion of the 2011 National Land Cover Database for the Conterminous United States – Representing a Decade of Land Cover Change Information. *Photogrammetric Engineering and Remote Sensing.*

Horowitz, C. A. (2016). Paris agreement. *International Legal Materials, 55(4),* 740-755. https://doi.org/10.1017/S0020782900004253

Intergovernmental Panel on Climate Change [IPCC]. (2021). 2021: summary for policymakers in climate change 2021: the physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu and B. Zhou (eds.)]. Cambridge University Press.

Kiesecker, J. M., Evans, J. S., Fargione, J., Doherty, K., Foresman, K. R., Kunz, T. H., Naugle, D., Nibbelink, N. P., & Niemuth, N. D. (2011). Win-win for wind and wildlife: a vision to facilitate sustainable development. *PLoS ONE 6(4)*: e17566. https://doi.org/10.1371/journal.pone.0017566

Kingsford, R. T. and J. L. Porter. (2009). Monitoring waterbird populations with aerial surveys – what have we learnt? *Wildlife Research 36*: 29-40. https://doi.org/10.1071/WR08034.

Koh, L. P. & Wich, S. A. (2012). Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. *Tropical Conservation Science 5(2):* 121-132. https://doi.org/10.1177/194008291200500202

Kuvlesky, Jr., W. P., Brennan, L. A., Morrison, M. L., Boydston, K. K., Ballard, B. M., & Bryant, F. C. (2007). Wind energy development and wildlife conservation: challenges and opportunities. *Journal of Wildlife Management 71(8)*: 2487-2498. https://doi.org/10.2193/2007-248.

Lin, T-Y., P. Goyal, R. Girschick, K. He, and P. Dollár. (2017). Focal loss for dense object detection. *Proceedings of the IEEE international conference on computer vision: 2980-2988*.

Linchant, J., Lisein, J., Ngabinzeke, J. S., & Lejeune, P. (2015). Are unmanned aircraft (UAS) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Review 45(4)*: 239-252. https://doi.org/10.1111/mam.12046.

Loss, S. R., Will, T., & Marra, P. P. (2013). Estimates of bird collision mortality at wind facilities in the contiguous United States. *Biological Conservation 168*: 201-209. https://doi.org/10.1016/j.biocon.2013.10.007.

Mathews, A. P. (2014). Renewable energy technologies: panacea for world energy security and climate change? *Procedia Computer Science (32):* 731-737. https://doi.org/10.1016/j.procs.2014.05.483

Mazerolle, M. J. (2020) AICcmodavg: model selection and multimodel inference based on (Q)AIC(c). R package version 2.3-1. <https://cran.r-project.org/package=AICcmodavg>.

North American Breeding Bird Survey [NABBS]. (2020). Weather Codes. Laurel, MD, USA: U.S. Geological Survey Patuxent Wildlife Research Center. <http://www.pwrc.usgs.gov/BBS/participate/training/appendixA.html>.

North Dakota Game and Fish Department [NDGF]. (2020). Tallgrass prairie (Red River Valley). Bismarck, ND, USA: North Dakota Game and Fish Department.
< https://gf.nd.gov/wildlife/habitats/tallgrass>.

Nichols, J. D. & Williams, B. K. (2006). Monitoring for conservation. *Trends in Ecology and Evolution 21(12):* 668-673. https://doi.org/10.1016/j.tree.2006.08.007.

Peters, K. & Farmer, C. (2018). Foxtail Wind Energy Center Wildlife Conservation Strategy. *Det Norske Veritas Germanischer Lloyd*. 116 pp.

Pöysä, H., Kotilainen, J., Väänänenm V., & Kunnasranta, M. (2018). Estimating production in ducks: a comparison between ground surveys and unmanned aircraft surveys. *European Journal of Wildlife Research 64(74)*. https://doi.org/10.1007/s10344-018-1238-2.

Rabie, P. A., Riser-Espinoza, D., Studyvin, J., Dalthorp, D., & Huso, M. (2021). Performance of the GenEst Mortality Estimator compared to the Huso and Shoenfeld Estimators. Washington, D.C.: American Wind & Wildlife Institute.

Ren, S., He, K., Girshick, R. and Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in Neural Information Processing Systems* (28):91-99

Reina, G. A., Panchumarthy, R., Thakur, S. P., Bastidas, A., & Bakas, S. (2020). Systematic evaluation of image tiling adverse effects on deep learning semantic segmentation. *Frontiers in Neuroscience 14(65)*. https://doi.org/10.3389/fnins.2020.00065

Reyes, G. A., Rodriguez, M. J., Lindke, K. T., Ayres, K. L., Halterman, M. D., Boroski, B. B., & Johnston, D. S. (2016). Searcher efficiency and survey coverage affect precision of fatality estimates. *Journal of Wildlife Management 80(8)*:1488-1496. https://doi.org/10.1002/jwmg.21126.

Rodhouse, T. J., Rodriguez, R. M., Banner, K. M., Ormsbee, P. C., Barnett, J., & Irvine, K. M. (2019). Evidence of region-wide bat population decline from long-term monitoring and Bayesian occupancy models with empirically informed priors. *Ecology and Evolution 9:*11078-11088. https://doi.org/10.1002/ece3.5612.

Rosa, I. M. D., Marques, A.T., Palminha, G., Costa, H., Mascarenhas, M., Fonseca, C., & Bernardino, J. (2016). Classification success of six machine learning algorithms in radar ornithology. *Ibis 158*: 28–42. https://doi.org/10.1111/ibi.12333.

Rosenberg, K. V., Dokter, A. M., Blancher, P. J., Sauer, J. R., Smith, A. C., Smith, P. A., Stanton, J. C., Panjabi, A., Helft, L., Parr, M., & Marra, P. P. (2019). Decline of the North American avifauna. *Science 366*: 120-124. https://doi.org/10.1126/science.aaw131.3

Shaffer, J. A. & Buhl, D. A. (2015). Effects of wind-energy facilities on breeding grassland bird distributions. *Conservation Biology 30(1)*: 59-71. https://doi.org/10.1111/cobi.12569.

Smallwood, K. S. (2013). Comparing bird and bat fatality-rate estimates among North American wind-energy projects. *Wildlife Society Bulletin 37(1):*19-33. https://doi.org/10.1002/wsb.260.

Smallwood, K. S., Bell, D. A., Walther, E. L., Leyvas, E., Standish, S., Mount, J., Karas, B. (2018). Estimating wind turbine fatalities using integrated detection trials. *Journal of Wildlife Management 82(6)*:1169-1184. https://doi.org/10.1002/jwmg.21468.

Smallwood, K. S. & Bell, D. A. (2020). Effects of wind turbine curtailment on bird and bat fatalities. *Journal of Wildlife Management 84(4)*:685-696. https://doi.org/10.1002/jwmg.21844.

Smith, G. W. (1995). A critical review of the aerial and ground surveys of breeding waterfowl in North America. Washington, D.C., USA: National Biological Service.

U.S. Fish and Wildlife Service [USFWS]. (2008). Comprehensive Conservation Plan – North Dakota Wetland Management Districts. Washington, D.C., USA: U.S. Fish & Wildlife Service.

U.S. Fish and Wildlife Service [USFWS]. (2012). U.S. Fish and Wildlife Service land-based wind energy guidelines. Washington, D.C., USA: U.S. Fish & Wildlife Service.

U.S. Fish & Wildlife Service [USFWS]. (2021). Threats to birds: migratory bird mortality – questions and answers. *U.S. Fish & Wildlife Service Migratory Bird Program*. < https://www.fws.gov/birds/bird-enthusiasts/threats-to-birds.php>.

Wargo, C.A., Church, G.C., Glaneueski, J., & Strout, M. (2014). Unmanned aircraft systems (UAS) research and future analysis. *2014 IEEE Aerospace Conference*, *Big Sky, MT, USA.*

Zhou, M., Elmore, J. A., Samiappan, S., Evans, K. O., Pfeiffer, M. B., Blackwell, B. F., & Iglay, R. B. (2021). Improving animal monitoring using small unmanned aircraft systems (sUAS) and deep learning networks. *Sensors 21(5697)*. https://doi.org/10.3390/s21175697.

Veers P., Dykes, K., Lantz, E., Barth, S., Bottasso, C., Carlson, O., Clifton, A., Green, J., Green, P, Holttine, H., Laird, D., Lehtomäk, V., Lundquist, J., Manwell, J., Marquis, M., Meneveau, C., Moriarty, P., Munduate, X., Muskulus, M., Naughton, J., Pao, L., Paquette, J., Peinke, J., Robertson, A., Rodrigo, J., Sempreviva, A., Smith, J., Tuohy, A., & Wiser, R. (2019). Grand challenges in the science of wind energy. *Science 366(6464)*. https://doi.org/10.1126/science.aau2027

Figures

Figure 1. Field locations used for collecting imagery of bird and bat carcasses in a variety of backgrounds and across seasons for the development of a convolutional neural network to detect bird and bat mortalities at wind energy sites. Field collection sites included a wind energy center in Dickey County, North Dakota and private lands in Grand Forks County, North Dakota between March – December 2020.

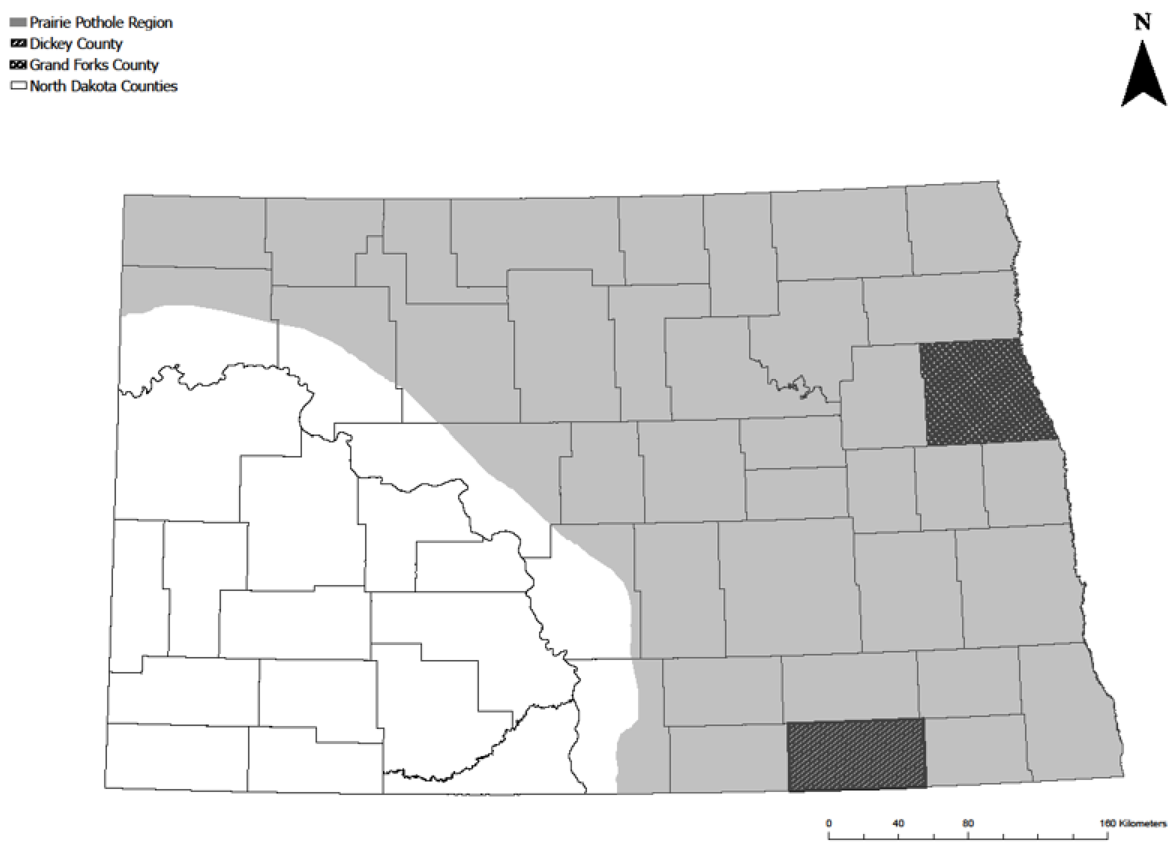


Figure 2. Software application created to label carcasses in unmanned aircraft system imagery for the development of a convolutional neural network to detect avian and bat mortality monitoring at wind energy centers in the midwestern United States. The application is able to create labels for the training of a neural network from user input data such as species, sex, and carcass condition.

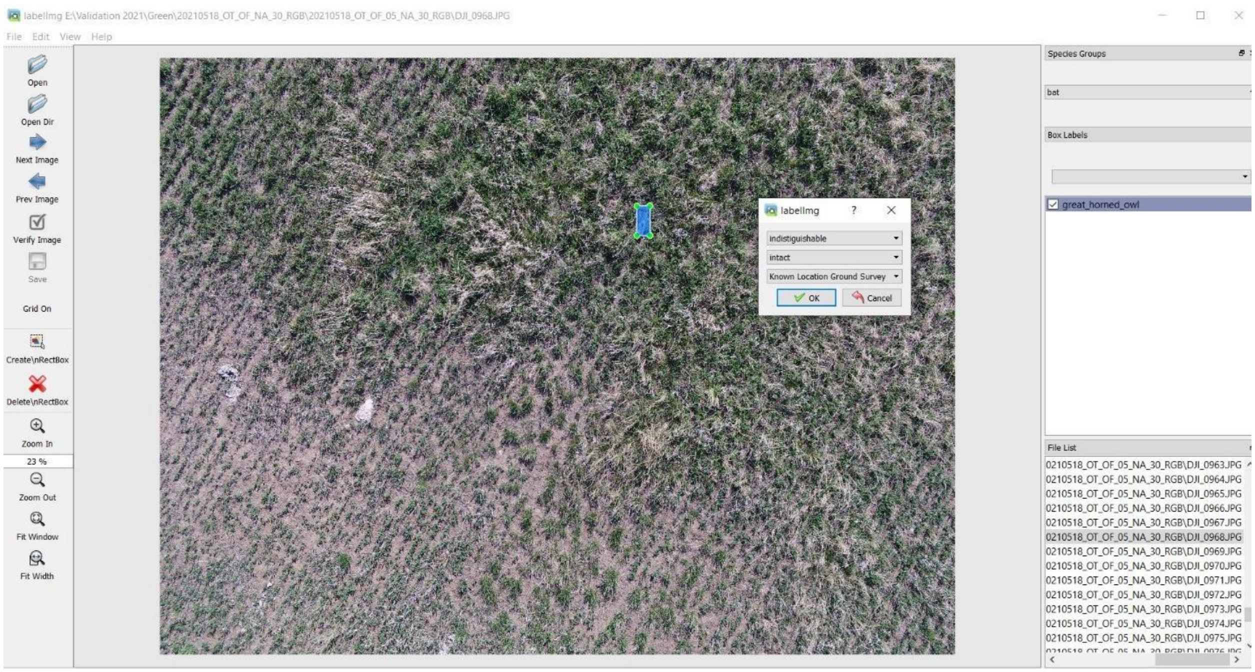


Figure 3. Means and +/- standard deviations of confidence estimates for true positive and false positive detections from a convolutional neural network trained to detect bird and bat carcasses. The area of non-overlap (95.9 – 97.2%) may be used to set a confidence threshold in future research to reduce the occurrence of false positives in the detection data.

CHAPTER III EXAMINING THE ACCURACY OF A CONVOLUTIONAL NEURAL NETWORK'S ABILITY FOR SPECIES IDENTIFICATION

Abstract

1. Successful population modeling is vital to understanding impacts from anthropogenic sources and climate change on vulnerable species and successful wildlife management. This is largely dependent upon accuracy in species identification and repeatable data collection methods. With recent advances in wildlife monitoring exploring machine learning for detection and classifying target objects, best practices for image collection must be implemented to yield high species identification accuracy.

2. Using a case study of convolutional neural networks trained for post-construction mortality monitoring of bird and bat carcasses at a wind energy center, we explored the relationships that accuracy in species identification have with environmental variables. Specifically, we coded different case scenarios of accuracy in species identification and used generalized linear models to relate this to sun angle, wind speed, sky cover, and species group.

3. Trained convolutional neural networks accurately identified species in 90.5% of image examples. Using AICc model selection, we found that the probability of accurate species identification was best described by sun angle and wind speed.

4. Probability of accurate species identification increased with increasing wind speed, as well as increasing sun angle.

5. *Synthesis and applications:* With this study, we showed that implementing convolutional neural networks for automation of species identification in a field monitoring scenario led to overall high accuracy rates with both environmental and image quality factors explaining higher

probabilities of correctness. Equipped with variables that influence species identification success, best practices for data collection can be employed to obtain improved data feeds at broader scales. This ultimately has the potential to create comparable data sets, better informing population models for interpreting species movement and distribution, diversity, and response to impacts from anthropogenic sources and climate change.

Keywords species identification, machine learning, classification, UAS, wildlife monitoring

INTRODUCTION

Species identification to understand distribution and population fluctuations is vital to informing proper wildlife and habitat management, particularly in the face of climate change where species are affected disproportionately and close monitoring may be necessary for responsive, accurate conservation decisions (Wilsey et al., 2019). Increasingly, wildlife biologists are turning to the use of remote sensing, camera trapping, and citizen science-captured imagery to explore the most efficient routes of monitoring wildlife for population surveys, regulatory compliance, behavior analysis, and beyond (Wargo et al., 2014, Pimm et al. 2015, Chabot et al., 2018, Poysa et al. 2018, Shah et al., 2021). Both remote sensing and citizen science platforms afford the opportunity to collect vast amounts of data in a repeatable, short period of time (Koh & Wich, 2012, Nguyen et al., 2017); however, great effort is dedicated on the backend to post-processing of imagery due to manual counting and identification of targets in thousands of images which can further delay responses to important conservation matters (Poysa et al. 2018). As such, the union of biologists and computer scientists has led to the construction of computer vision systems for rapid image processing that can produce highly accurate detection data (Pimm et al., 2015, Ward et al., 2016, Nguyen et al., 2017, Seymour et al., 2017, Van Horn et al., 2018).

Researchers have begun working on accurate species identification using image-based classification systems, but more effort is needed to understand and implement automated species identification in true field settings for standardized, repeatable data collection that allow for comparison of impactful, unbiased results (Piorkowski et al., 2012, Gula & Theuerkauf, 2013). Current work largely focuses on imagery taken in a lab environment or by novice observers where imbalanced class sizes and lack of uniformity in image capture techniques can present problems in classification accuracy (Van Horn et al. 2018). Fewer algorithms, such as the use of the U.S. Fish & Wildlife Service Feather Atlas for automating airport runway avian collision species parts identification, have been developed for standardized methodology in field research applications (Wäldchen & Mäder, 2018, Shah et al., 2021). Image classification for field-based research has more commonly involved the automation of remotely sensed imagery for purposes of detection and counting of individual study species (Chabot et al. 2018), leaving the difficulties of species identification when studying multiple species left to navigate. This is particularly important in scenarios such as mortality monitoring of birds and bats at wind energy centers, airports, or in oil spills, where monitoring is widespread and many species may be observed with some protected by regulations such as the Endangered Species Act, Bald and Golden Eagle Act, or the Migratory Bird Treaty Act (Piorkoswki et al., 2012). Research has shown that factors such as sun angle, weather variables, size, coloration, and land cover type can all play a role in the detection of a target of interest in remotely sensed photographs (Linchant et al., 2015, Reina et al., 2020, Yannuzzi Chapter 2), but little has been done to explore how these variables play a role in the success and confidence of species identification. Examining these factors may aid in future standardization of image collection and automation to more accurately identify species and employ these survey techniques at a broad-scale to achieve rapid, repeatable, meaningful scientific query and monitoring.

We investigated the variables that may play a role in the accuracy of a trained neural network's species identification using a case study of a convolutional neural network trained for the detection of avian and bat mortalities at wind energy centers (Yannuzzi et al. in review). We hypothesized that larger species groups (i.e., raptors, waterfowl) would increase accuracy in species identification, while smaller birds and bats, higher wind speeds, low sun angle, and clear skies would likely decrease accuracy in species identification (Linchant et al., 2015, Reina et al., 2020, Yannuzzi Chapter 2). With this knowledge, we provided recommendations for improving standardization of future image collection and deep learning techniques to improve species identification for wildlife monitoring and conservation priorities.

METHODS

Between March and mid-December 2020 in North Dakota, USA, we collected remotely sensed imagery of carcasses from 51 bird species and 5 bat species at a wind farm and similar habitat within a variety of ground cover types (i.e., snow, crop, dirt/gravel, pasture). We used a DJI Matrice 210 v2 RTK (color: black, weight: 4.8kg, operating temp: -20°C to 50°C) to fly lawnmower grid surveys at 9.14 m above ground at a speed of 1.8 m/s, capturing imagery with a DJI Zenmuse X5S camera (RGB) with a 50% overlap producing multiple images of some carcasses (Yannuzzi et al. in review). Biological experts labeled carcasses in imagery by drawing boxes over known-location carcasses and associating labels to species, sex, and carcass condition (i.e., intact, scavenged, dismembered, feather spot), along with flight survey-level variables including: season (i.e., spring, summer, fall), time of day, latitude and longitude, derived sun angle incorporating azimuth and elevation (Cornwall et al., 2020), sky cover (NABBS, 2021), and surrounding ground cover within 5 m of the carcass. We also labeled non-target items that we expected might pose problems for detection and species identification such as landscaping cloth, categorizing them as "garbage"; however, we did not incorporate this category into the analysis of this study. We used a RetinaNet (Lin et al., 2017) object detection CNN model for the detection task which utilizes a ResNet (He et al., 2016) CNN as a backbone structure. We trained two models, one for each background color: Brown (dirt/gravel, spring and fall vegetation) and Green (summer vegetation). We used a roughly 80% training/20% validation image split. Splits were done by utilizing a randomized method which repeatedly attempted to assign images to the training and validation sets such that the number of target examples for each class had an 80%/20% split. We used this method as this task is not trivial when an image can have multiple bounding boxes of different types within them, and in many cases, it is not possible to get perfect training/validation splits across all classes. We split 1,634 source brown background images into 1,312 training images and 322 validation images, and split 173 source green background images into 127 training images and 36 validation images. Appendix B shows the class types and numbers of example images of each class in each training set.

Training the RetinaNet used a custom training pipeline developed by Thread, which generates training samples for each epoch of training the CNN by randomly selecting windows around bounding boxes in the training imagery. After that, the training images are passed through a series of data augmentations from the open source Albumentations library (Buslaev et al., 2018). For this work, we used the window size 400 x 400, followed by the RandomBrightnessContrast (50% application, brightness and contrast limits of 0.2) and Perspective (100% application, scale minimum and maximum values of 0.05 and 1.0) transforms. Because of these random data augmentations, images fed to the network during training were always different modified sub-windows of the training images. Validation and inference were performed by striding the trained RetinaNet over 400x400 windows (with a user-specified overlap, in this case 20 pixels) in the target images and then merging the predicted bounding boxes if class types were the same and the bounding boxes overlapped by at least 50%.

Using a subsample of test results from the same data set (Brown = 302 carcasses, Green = 4 carcasses; Yannuzzi et al. in review), we modeled how neural networks identified species in UAS imagery from a wind energy mortality monitoring case study to determine what variables impact accurate species identification. Therefore, we split the response variable of species identification into four case scenarios of best to worst case scenario, wherein true positives were the best-case scenario, followed by partial correctness, incorrectness, and false negative being the worst case scenario (Table 1) to group different levels of confidence. Using these scenarios, we implemented generalized linear models to relate species identification to derived sun angle (Cornwall et al. 2020), wind speed (mph), sky cover (NABBS, 2021), and species group (i.e., waterbird, cranes/rails, gulls/terns, pigeons/doves, raptor, songbird, shorebird, upland gamebird, waterfowl, woodpecker, and bat).

Using program R version 4.0.1.0, we built three candidate generalized linear models with a gaussian distribution including fixed effects: a null model, a global model (i.e., sun angle [azimuth * elevation], wind speed, sky cover, species group), and a reduced model (i.e., sun angle [azimuth * elevation], wind speed) (Table 2). We then used the AICcmodavg package (Mazerolle, 2020) to perform Akaike's Information Criterion model selection adjusted for small sample sizes (AICc) to select a top model from the candidate list.

RESULTS

Overall, accuracy in species identification was high with 90.52% true positives. False negatives accounted for 1.31%, with partially correct identification totaling 5.23% and incorrect identification totaling 2.94%. Using generalized linear models and AICc model selection, we determined that the reduced model, including wind speed (mph) and sun angle, best explained the accuracy in species identification. We detected no competing models (ΔAICc value <2).

The likelihood of achieving a best case scenario (i.e., true positive) of species identification increased with increasing windspeed ($ß=0.1$, $SE = 0.04$, $p < 0.05$), and also increased with increasing sun angle ($ß=0.0003$, $SE = 0.0002$, $p < 0.05$).

DISCUSSION

We evaluated species identification accuracy and influencing environmental and image quality variables in a convolutional neural network developed for a post-construction mortality monitoring scenario. Accurate, real-time, automated species identification in remotely sensed imagery has enormous implications for conservation, particularly for at risk species where impacts on small, vulnerable populations need to be as precise as possible (Hunter et al., 2019). With this technology, previously daunting data collection scenarios can occur rapidly with high accuracy in areas that may be inaccessible by humans without risking human safety and minimizing disturbance on the land and wildlife (Brisson-Curadeau et al., 2017, Pirotta et al. 2017, Duporge et al., 2021). Rapid response to estimate anthropogenic impacts to individual species, wildlife health surveying, behavioral analysis, or routine population monitoring (Brisson-Curadeau et al. 2017, Pirotta et al. 2017, Hunter et al. 2019) have the potential to help wildlife managers curtail negative impacts on vulnerable species.

While automated detection and species identification are crucial to accurate and swift action when needed, it is vital to understand practices for image collection that achieve the best results. Data collection may require extended field seasons to capture adequate generalization of environmental variables in imagery. Our findings indicate that successful species identification depends on environmental situations surrounding imagery collection. Image collection should occur days with wind speeds between five and nine mph, ideally in the morning or afternoon. These environmental variables likely impact species identification due to their role in the amount of reflectance, shadowing, and image blur that is prone to occur when the sun and wind are most intense (Dare, 2005, Sayed & Brostow, 2021). While wind had a positive association with increasing accuracy in species identification, confidence in this accuracy begins to decrease around wind speeds of 10 mph, likely due to increased vegetation movement and decreased aircraft stabilization, resulting in more image blur. Wind speeds and time of day when collecting imagery should be considered when building convolutional neural networks for species identification needs to obtain the most exact data possible.

Accuracy in species identification directly translates to improved data feeds and well-informed population models. This can help aid conservation biologists in understanding the effect of climate change on a species, species richness and diversity, status of endangered species, anthropogenic impacts on species, species distribution, and more (Wäldchen & Mäder, 2018). Automation of species detection and identification from remotely sensed imagery allows for better access and results to previously difficult to obtain data whether that be due to impassable terrain, human safety, or disturbance. While this is exciting progress in the realm of wildlife monitoring, imagery used to train machine learning algorithms must be collected with best, standardized practices in mind to allow for generalizing so that larger, regional datasets can be compared for meaningful results.

ACKNOWLEDGMENTS

The authors are thankful to funding sources from the North Dakota Department of Commerce (Award: 19-11-G-229), University of North Dakota, Microsoft AI for Earth Grant (Award: MS-AZR-0036P), and the AmericaView North Dakota View Scholarship (USGS grant G18AP00077). We are grateful for our partnerships and input from Xcel Energy, North Dakota Department of Game and Fish, and the U.S. Fish and Wildlife Service.

LITERTURE CITED

Brisson-Curadeau, E., Bird, D., Burke, C., Fifield, D. A., Pace, P., Sherley, R. B., & Elliott, K. H. (2017). Seabird species vary in behavioural response to drone census. *Scientific Reports 7:17884.* https://doi.org/10.1038/s41598-18202-3

Chabot, D., Dillon, C., & Francis, C. M. (2018). An approach for using off-the-shelf object-based image analysis software to detect and count birds in large volumes of aerial imagery. *Avian Conservation & Ecology 13(1):15*. https://doi.org/10.5751/ACE-01205-130115

Cornwall, C., Horiuchi, A., & Lehman, C. (2020). Solar position calculator. *Boulder, CO, USA: National Oceanic and Atmospheric Administration: Earth Systems Research Lab*. <https://esrl.noaa.gov/gmd/grad/solcalc/>.

Dare, P. M. (2005). Shadow analysis in high-resolution satellite imagery of urban areas. *Photogrammetric Engineering & Remote Sensing 71(2):169-177.* https://doi.org/10.14358/PERS.71.2.169

Duporge, I., Spiegel, M. P., Thomson, E. R., Chapman, T., Lamberth, C., Pond, C., Macdonald, D. W., Wang, T., & Klinnk, H. (2021). Determination of optimal flight altitude to minimise acoustic drone disturbance to wildlife using species audiograms. *Methods in Ecology and Evolution 00:1-12.* https://doi.org/10.1111/2041-210X.13691

Gula, R. & Theuerkauf, J. (2013). The need for standardization in wildlife science: home range estimators as an example. *European Journal of Wildlife Research 59:713-718.* https://doi.org/10.1007/s10344-013-0726-7

Huang, B., Reichman, D., Collins, L. M., Bradbury, K., & Malof, J. M. (2018). Tiling and stitching segmentation output for remote sensing: basic challenges and recommendations. *arXIV Preprint arXIV:1805.12219.*

Hunter, S. A., Tennyson, A. J. D., Bartle, J. A., Miskelly, C. M., Waugh, S. M., McConnell, H. M., Morgan, K. J., Finlayson, S. T., Baylis, S. M., Chilvers, B. L., & Gartrell, B. D. (2019). Assessing avian mortality during oil spills: a case study of the New Zealand MV 'Rena' oil spill, 2011. *Endangered Species Research 39:303-314.* https://doi.org/10.3354/esr00974.

Koh, L. P. & Wich, S. A. (2012). Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. *Tropical Conservation Science 5(2):*121-132. https://doi.org/10.1177/194008291200500202

Korstien, J. M., Hale, A. M., Bennett, V. J., & D. A. Williams. 2016. Using DNA barcoding to improve bat carcass identification at wind farms in the United States. *Conservation Genetics Resources* 8: 27-34.

Linchant, J., Lisein, J., Semeki, J., Lejeune, P., & Vermeulen, C. (2015). Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Review 45(4):239-252.* https://doi.org/10.1111/mam.12046

Mazerolle, M. J. (2020) AICcmodavg: model selection and multimodel inference based on (Q)AIC(c). *R package version 2.3-1*. <https://cran.r-project.org/package=AICcmodavg>.

North American Breeding Bird Survey [NABBS]. (2021). Weather Codes. *Laurel, MD, USA: U.S. Geological Survey Patuxent Wildlife Research Center*. <http://www.pwrc.usgs.gov/BBS/participate/training/appendixA.html>.

Nguyen, H., Maclagan, S.J., Nguyen, T.D., Nguyen, T., Flemons, P., Andrews, K., Ritchie, E.G. & Phung, D. (2017). Animal recognition and identification with deep convolutional neural networks for automated wildlife monitoring. *2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA):40-49.* https://doi.org/10.1109/DSAA.2017.31

Pimm, S. L., Alibhai, S., Bergl, R., Dehgan, A., Giri, C., Jewell, Z., Joppa, L., Kays, R., and S. Loarie. (2015). Emerging technologies to conserve biodiversity. *Trends in Ecology & Evolution 30(11):685-696*. https://doi.org/10.1016/j.tree.2015.08.008

Piorkowski, M. D., Farnsworth, A. J., Fry, M., Rohrbaugh, R. W., Fitzpatrick, J. W., & Rosenberg, K. V. (2012). Research priorities for wind energy and migratory wildlife. *Journal of Wildlife Management 76(3):451-456.* https://doi.org/10.1002/jwmg.327

Pirotta, V., Smith, A., Ostrowski, M., Russell, D., Jonsen, I. D., Grech, A., & Harcourt, R. (2017). An economical custom-built drone for assessing whale health. *Frontiers in Marine Science 4(425).* https://doi.org/10.3389/fmars.2017.00425

Poysa, H., Kotilainen, J., Vaananen, V., & Kunnasranta, M. (2018). Estimating production in ducks: a comparison between ground surveys and unmanned aircraft surveys. *European Journal of Wildlife Research 64(74).* https://doi.org/10.1007/s10344-018-1238-2

Reina, G. A., Panchumarthy, R., Thakur, S. P., Bastidas, A., & Bakas, S. (2020). Systematic evaluation of image tiling adverse effects on deep learning semantic segmentation. *Frontiers in Neuroscience 14(65)*. https://doi.org/10.3389/fnins.2020.00065

Ren, S., He, K., Girshick, R. and Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in Neural Information Processing Systems (28):91-99. arXiv: 1506.01497v3.*

Sayed, M., & Brostow, G. (2021). Improved handling of motion blur in online object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition: 1706-1716. arXiv: 2011.14448*

Seymour, A. C., Dale, J., Hammill, M., Halpin, P. N., & Johnston, D. W. (2017). Automated detection and enumeration of marine wildlife using unmanned aircraft systems (UAS) and thermal imagery. *Scientific Reports 7:45127*. https://doi.org/10.1038/srep45127

Shah, M., Nagda, K., Mukherjee, A. and Kanani, P. (2021). Application of Convolutional Neural Network in Feather Classifications. In *Design of Intelligent Applications Using Machine Learning and Deep Learning Techniques* (pp. 223-232). Chapman and Hall/CRC.

Van Horn, G., Mac Aodha, O., Song, Y., Cui, Y., Sun, C., Shepard, A., Adam, H., Perona, P. & Belongie, S. (2018). The iNaturalist species classification and detection dataset. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 8769-8778). arXiv: 1707.06642

Venables, W. N. & Ripley, B. D. (2002). Modern applied statistics with S. 4th ed. Springer, New York.

Wäldchen, J. & Mäder, P. (2018). Machine learning for image based species identification. *Methods in Ecology and Evolution 9:2216-2225*. https://doi.org/10.1111/2041-210X.13075

Ward, S., Hensler, J., Alsalam, B., and Gonzalez, L. F. 2016. Autonomous UAVs wildlife detection using thermal imaging, predictive navigation and computer vision. In Mattingly, R (Ed.) *Proceedings of the 2016 IEEE Aerospace Conference*: 1812-1818. https://doi.org/10.1109/AERO.2016.7500671

Wargo, C. A., Church, G. C., Glaneueski, J., & Strout, M. (2014). Unmanned aircraft systems (UAS) research and future analysis. *2014 IEEE Aerospace Conference, Big Sky, MT: 16 pp.* https://doi.org/10.1109/AERO.2014.6836448

Wilsey, C., Taylor, L., Bateman, B., Jensen, C., Michel, N., Panjabi, A., & Langham, G. (2019). Climate policy action needed to reduce vulnerability of conservation-reliant grassland birds in North America. *Conservation Science and Practice 1(e21)*. https://doi.org/10.1111/csp2.21

Yannuzzi, S., ElSaid, A., Desell, T. J., Riedy, J., Sather, B. M., Westrem, J., & Ellis-Felege, S. N. (2021). Developing and evaluating a convolutional neural network to assess remotely sensed imagery for bird and bat mortality monitoring at wind energy sites. *Manuscript in review submitted to the Journal of Applied Ecology.*

TABLES & FIGURES

Table 1. Species identification case scenario codes and corresponding definitions to examine the way that trained machine learning models identified bird and bat species in a wind energy mortality monitoring case study.

Species Identification Code	Definition
Best case scenario: true positive	Only the correct species was identified
Second best-case scenario: partially correct	Two or more species were identified and one was the correct species
Third best-case scenario: incorrect	One or more species were identified and none were the correct species
Worst case scenario: false negative	No target was identified but was available for detection

Table 2. Candidate list of multinomial models to evaluate how environmental and image quality variables relate to accuracy in species identification ranked by lowest AIC.

Model Name	Model Parameters	K	AIC	ΔAIC	Model Weight
Reduced	Wind Speed + Sun Angle	6	447.08	0.00	1.00
Global	Sky Cover[1] + Species Group[2] + Wind Speed + Sun Angle	18	464.66	17.58	0.00
Null	Intercept-only	2	466.04	18.96	0.00

[1]Sky cover categories: clear or few clouds, partly cloudy, overcast, fog or smoke, light rain, snow, showers

[2]Species group categories: waterbird, cranes/rails, gulls/terns, pigeons/doves, raptor, songbird, shorebird, upland gamebird, waterfowl, woodpecker, and bat

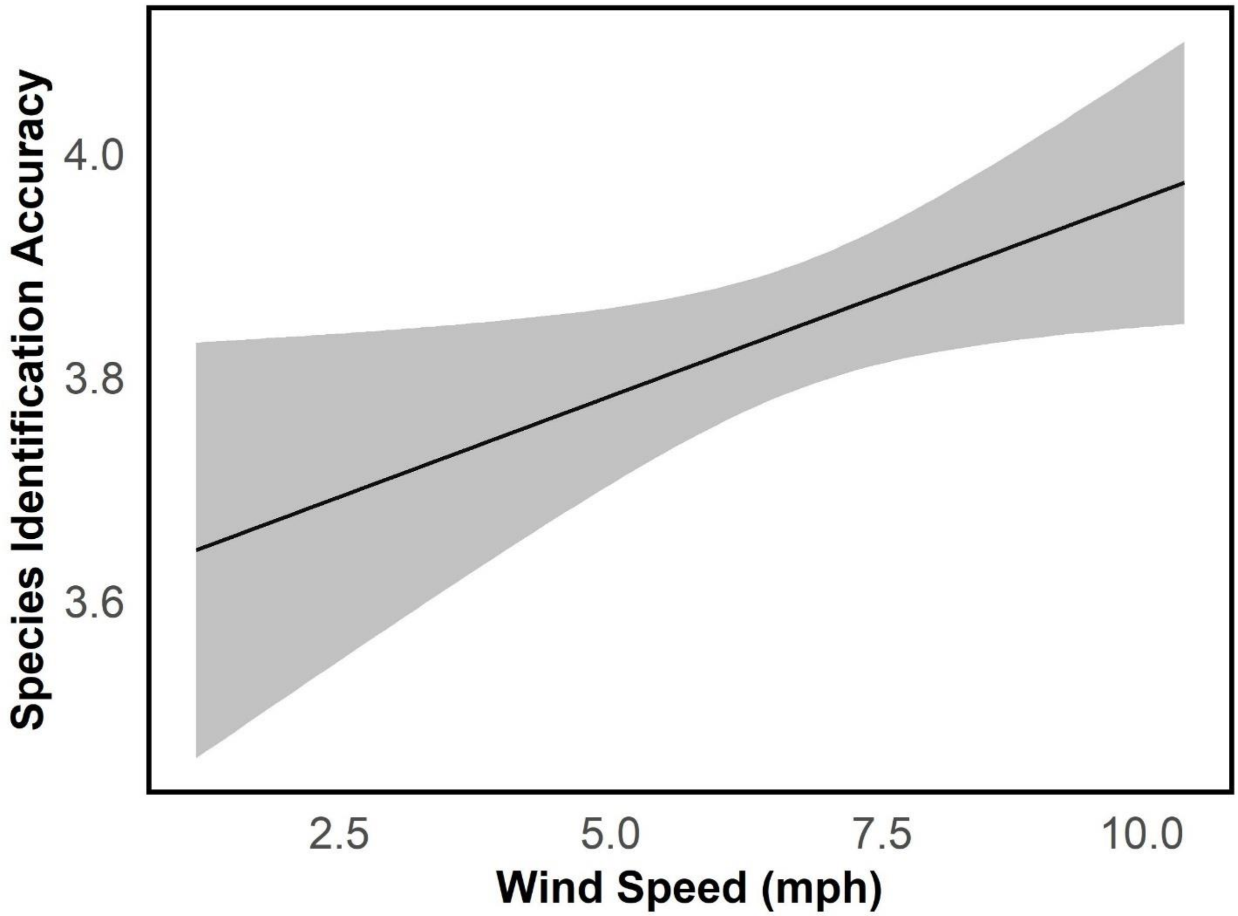


Figure 1**.** Species identification accuracy with 95% confidence intervals presented as best (4) to worst (1) case scenario in relation to wind speed (mph) from convolutional neural network models built for bird and bat carcass detection during post-construction mortality monitoring at wind energy centers. Best case scenario (true positive; 4) = only the correct species was identified; Second best scenario (partial correctness; 3) = 2+ species were identified, and one was the correct species; third best scenario (incorrectness; 2) 1+ species were identified, and none were the correct species; worst case scenario (1; false negative) = no target was identified but was available for detection.

CHAPTER IV COMPARING DETECTION RATES OF BIRD AND BAT FATALITIES BETWEEN GROUND SURVEYORS AND A TRAINED CONVOLUTIONAL NEURAL NETWORK

ABSTRACT

Renewable energy is rapidly growing in the United States and beyond. With increasing energy construction leaves the potential for increased impacts on wildlife, particularly bird and bat species. For newly constructed energy facilities where uncommon species or rare events are of concern, a refined probability of detection is needed to increase confidence in fatality estimates. Human searchers are commonly used at these facilities to perform post-construction monitoring of bird and bat species, but are typically not as efficient as needed in detection and time for projects with higher targets of probability of detection. Aiming to improve efficiency, we previously developed machine learning algorithms through convolutional neural networks (CNN) to detect bird and bat fatalities from imagery taken by uncrewed aircraft systems equipped with a color sensor. Initially achieving an average detection rate of 98.7% during validation, we aimed to test detection rates of the CNN against ground searchers commonly used for post-construction monitoring. We performed side-by-side searches of 60 plots in spring, summer, and fall, and varying ground cover types (e.g., crop, dirt/gravel, and pasture). Ground surveyor detection was comparable to previously published rates at 63%, while the CNN's detection was much lower than the initial validation phase at 29%. We also examined factors that were influential in the detection data using generalized linear mixed models, finding that ground surveyor detection was informed by carcass density within a plot and carcass size class. CNN detection was similarly informed by carcass density within a plot and carcass size class, in addition to vegetative visual obstruction and ground cover. While initial phases of development of this CNN show strong promise for highly refined results for probability of detection

estimation, further development of the model is needed by continued training with increased quantities of species and ground cover types. Additionally, future exploration of sensor combinations and generalization amongst sensors may allow for easier adaptation of the trained CNN as technology advances.

INTRODUCTION

Post-construction mortality monitoring (PCMM) is often required for at least one year following construction of a wind energy center by state and federal agencies in compliance with the Migratory Bird Treaty Act, the Bald and Golden Eagle Act, the Endangered Species Act, and the National Environmental Policy Act (USFWS 2012). Mortality information gleaned from PCMM work is used to inform future site-specific wildlife monitoring and mitigation efforts, along with siting of future renewable energy centers. Further, fatality estimates at local and regional scales of bird and bat species are incorporated into population management, regulations, and conservation initiatives. This work is outsourced by energy companies to environmental consulting groups that employ biologists to perform carcass searches for estimating fatality rates, searcher efficiency trials for evaluating surveyor detection rates and biases, and carcass persistence trials as an additional bias correction estimate determining how long carcasses remain on the landscape prior to scavenger removal or decay (USFWS 2012).

Traditional survey methodology of carcass searches varies among consulting groups and wind facilities but is based on guidelines provided by the USFWS Land-Based Wind Energy Guidelines (USFWS 2012). Typically, carcass searches are performed more intensively at a subset of wind turbines, with biologists walking lawnmower grid transects within a designated radius of a tower cleared of vegetation (hereafter, “cleared plots”), and walking roads and pads within 100 m of a tower at all remaining turbines (USFWS 2012). Despite this, human detection rates average 65% and vary greatly depending on carcass size, with bat detection estimates of 14-42% depending on the site conditions (Arnett 2006, Mathews et al. 2013, Barrientos et al. 2018). Increasingly, canine detection teams have been incorporated into these search protocols to boost detection rates of survey teams. With the addition of canines, detection rates increase to an average of 87% (Barrientos et al. 2018) and decrease search time threefold (humans: 2 hr 46 min vs. dogs: 40 min; Mathews et al. 2013). Human detection rates are thought to be influenced by experience level, fatigue, visibility conditions within cover types, carcass type and size, season, and environmental conditions (Ransom et al. 2012, Mathews et al. 2013, Reyes et al. 2016, Barros et al. 2021). Dogs, too, show variability in their detection relative to environmental conditions, ground cover, topography, physical fitness, and handler error (Mathews et al. 2013, Barrientos et al. 2018). These varying detection rates, particularly where human searchers are involved, can result in uncertainty in fatality estimates, which can be problematic when fatality counts are close to or at zero (Mathews et al. 2013).

Uncrewed aircraft systems (hereafter, UAS) are used for ecological research to improve efficiency in data collection (Wargo et al. 2014), covering difficult terrain quickly in a repeatable manner (Koh and Wich 2012, Floreano and Wood 2015). Despite this, there are still limitations associated with UAS platforms in ecological research. Humans are needed to review imagery taken by UAS and search for target objects within, which can be a time intensive and tedious task and introduces additional sources of error (Poysa et al. 2018). Further, visual obstructions from vegetation or shadows within imagery may reduce visibility and likelihood of detection in imagery within certain environments.

Pairing UAS imagery with a trained convolutional neural network (CNN) may provide further efficiency in UAS-collected ecological research, particularly as it applies to post-construction mortality monitoring. CNNs are a type of machine learning that can be trained to perform object detection and classification within a dataset. They require training on datasets prior to implementation to learn what the target of interests are and reduce the occurrence of false positives. Many factors, such as cover type, weather, sun angle, size, coloration, can play a role in the accuracy of detections and classification of target objects (Linchant et al. 2015). As such, proper preparation of a CNN through exposure to increased and diverse training data sets is vital for better educating a CNN, which increases the likelihood of success (Linchant et al. 2015, Rosa et al. 2016). With adequate computational power, a well-trained CNN can provide near real-time data to users, which reduces manual image processing time. Recent research has employed this technology, using UAS paired with trained convolutional neural networks (CNN) to detect and classify bird and bat mortalities, leading to promising increases in detection rates as high as 98% (S. Yannuzzi unpublished data).

However, to gain industry and regulatory acceptance, this technique must perform similarly or better than currently accepted ground survey methods. If successful, this technique has the potential to greatly increase the quality of important wildlife population data feeds alongside increased efficiency for industry. Higher detection rates create less uncertainty in fatality estimates and if adopted, consistency in survey methodology may allow for comparable datasets at widespread scales, producing more meaningful results and better-informed management. As such, we aim to provide proof of concept for a trained CNN to determine if adoption into industry and regulatory standards is feasible by estimating detection rates for this technique compared to traditional ground surveyors. We also aim to explore environmental and experience-based factors impacting detection of bird and bat carcasses by ground surveyors. Specifically, we want to know 1) how traditional ground surveyor methods compare to a trained

CNN in detecting bird and bat carcasses and 2) how detection by ground surveyors is influenced by environmental factors and experience level. We hypothesize that 1) the CNN will have a higher average detection rate of both bird and bat carcasses than the ground surveyor, but that ground surveyors will perform better in areas of heavy vegetation than the CNN due to obstructed visibility from the nadir position of image capture; and 2) the ground surveyor detection rates will decrease as wind speed, temperature, and vegetative cover increases, as experience level and sun angle decrease, on clear sky days, and in plots with fewer and smaller carcasses. With this, we hope to not only provide a feasibility study, but also better unpack situations in which certain methods may be more effective than others to provide biologists improved guidance in method selection.

STUDY AREA

We selected four locations within North Dakota to collect data. These sites were chosen to represent the variety of habitat, vegetation, soil, and cover types available within the state: McKenzie County, Grand Forks County, Pembina County, and Rolette County. The study sites span the Northwestern Great Plains, Lake Agassiz Plain, and Northern Glaciated Plains Ecoregion Level III (USEPA 2013). The Northwestern Great Plains includes McKenzie County and is largely unglaciated plain of shale, siltstone, and sandstone with scattered buttes and badlands. Ground cover is predominantly rangeland and native grassland, with some wheat and alfalfa farming restricted by unpredictable precipitation and areas of steep topography. Grand Forks County and most of Pembina County lies within the Lake Agassiz Plain, a region of flat lake sediment atop glacial till, which consisted of tallgrass prairie pre-settlement, but was converted to row crop agriculture. Common crops are sugar beets, corn, soybeans, wheat, and potatoes. The Northern Glaciated Plains, where Rolette County lies, is glacial drift containing transitional grassland between short and tallgrass prairie, with agricultural activities constrained by annual weather cycles (USEPA 2013).

METHODS

FIELD METHODS

Paired Surveys - We performed paired surveys of preprogrammed UAS flights near simultaneous to ground searches at four sites within North Dakota in the spring (15 April - 31 May 2021), summer (15 June - 31 July 2021), and fall (1 September - 15 October 2021). Within each season, we performed surveys in 60 plots divided into three cover types (20 pasture, 20 dirt/gravel, and 20 crop). All plots were 120 x 120 m in size (hereafter, "full plots") to simulate cleared plot searches at wind facilities, except for dirt/gravel plots wherein we further divided the 20 plots into 10 full plots and 10 100 m x 15 m plots to simulate searches performed along roads within the vicinity of a turbine tower (hereafter, "road plots"). Of the 20 plots within each cover type, we defined half (10) as high-density plots with 10 - 15 carcasses placed within them, and half (10) as low-density plots with 1 - 5 carcasses placed within them. Dirt/gravel cover type plots were divided similarly with 5 high-density full plots, 5 low-density full plots, 5 high-density road plots, and 5 low-density road plots.

We placed bird and bat carcasses with unique ID codes indicating taxa and individual on tags affixed to a leg in known locations within each plot (Table 1). Tags were obscured from aerial visibility to avoid detection of those by the CNN. We performed surveys between 0700 and 1800 hrs. We equipped each observer with a handheld GPS preprogrammed with plot boundaries and 6 m wide lawnmower grid tracks to follow (Garmin BaseCamp version 4.7.4). Observers recorded location, time of day (morning = 0600 - 1100 hrs, midday = 1101 - 1600 hrs, evening = 1601 - 2100 hrs), highest educational degree, whether or not they had relevant survey experience and the number of months of experience, along with survey start and stop time, wind speed (mph) and direction, temperature (°C), sky cover (NABBS 2022), and the carcass unique ID code for each target found.

Near simultaneously (i.e., within the hour of the ground search start), we flew a DJI Matrice 210 v2 RTK (color: black, weight: 4.8kg, operating temp: -20°C to 50°C) with a DJI Zenmuse X5S 15 mm camera (RGB) sensor within the same plots at 9.14 m above ground level at 1.8 m/s with 70% overlap. We chose the flight height to simulate that of the safe flight zone below the rotor swept area of a moving wind turbine and to mirror the flight parameters under which the CNN was trained. We included a high overlap of images to allow for increased collection of data for use in any further CNN model training if deficiencies were detected post-testing. With each UAS survey, we collected information including: date, pilot in command, time of day, flight number, altitude (ft), start and stop time, wind speed (mph) and direction, sky cover (NABBS 2022), and temperature (°C).

Vegetation Surveys - We collected vegetation metrics once per every survey week within each plot per season. Using a Robel pole with alternating colors of decimeters marked, we took visual obstruction readings (VOR) in the four cardinal directions (Robel et al. 1970), and vegetation height at three points moving diagonally within the plot, the centroid and two opposing corners. VOR readings were made by reading the lowest visible decimeter from 1 m high and 4 m (Robel et al. 1970), whereas vegetation heights were read from the same position but recording the decimeter with the general height within the approximately 5 m around the sample point.

ANALYSIS

Convolutional neural network - Following methods used in Chapter II, we drew boxes around known-location carcasses and labeled each with corresponding species and species group. If a carcass was unavailable to be found in imagery for labeling due to vegetation obstruction or camouflage, it was removed from the dataset to be certain whether a carcass was detected or missed by the CNN. We then tested the CNN that was trained and validated in Chapter II on the new set of images.

Statistical Analysis -

Ground Surveyors – We treated ground surveyor data as binary detection, 0 (carcass was not detected) and 1 (carcass was detected). We implemented package lme4 (version 1.1-31) in program R version 4.2.2 to build five candidate binomial generalized linear mixed models with observer as a random effect including: an intercept-only model, a carcass characteristics model (carcass density, carcass size class), a plot characteristics model (ground cover, VOR, vegetation height), a seasonal characteristics model (wind speed, temperature, sky cover, season), and an observer experience model (months of experience, days spent surveying). We then used the AICcmodavg package (Mazerolle 2020) to perform Akaike's Information Criterion model selection adjusted for small sample sizes (AICc) to select a top model from the candidate list.

Convolutional Neural Network – Due to image overlap, carcasses appeared in an inconsistent number of images. As a result, we treated CNN data as the total number of successful detections out of the total number of possible detections. We implemented package lme4 (version 1.1-31) in program R version 4.2.2 to build four candidate binomial generalized linear mixed models with plot as a random effect, including: an intercept-only model, a carcass characteristics model (carcass density, carcass size class), a plot characteristics model (ground cover, VOR), and a global model. We then used the AICcmodavg package (Mazerolle 2020) to perform Akaike's

Information Criterion model selection adjusted for small sample sizes (AICc) to select a top model from the candidate list.

RESULTS

In total, 951 carcasses were located during the image labeling process and incorporated into the dataset. Four-hundred thirty large birds were available to be found, 357 small birds, and 164 bats across 59 species, 55 unique plots, and nine ground surveyors. Individual carcasses were available to be found by the CNN in an average of four images (range: 1– 16). Seven-hundred forty-three carcasses were in high density plots and 208 were in low density plots. Average VOR within plots was 0.91 dm (range: 0 – 3.25 dm), with carcasses in 372 dirt/gravel plots, 254 plots in cropland plots, and 325 in pasture plots. Image reviewers were unable to locate 175 additional carcasses, largely small birds and bats, for labeling in imagery and as such, these carcasses were excluded from the analysis as we would be unable to confirm without a doubt that a detection by the CNN was one of these carcasses.

The average detection rate of the trained CNN was 28.86%, while the average detection rate of the ground surveyors was 63.17%. Average detection rate for carcass species that were used in the initial training of the CNN was 26.89% (range: 0-100%, n = 684), and average detection rate for carcass species novel to the CNN was 33.92% (range: 0-100%, n = 267). Detection by ground surveyors was best explained by the carcass characteristics model variables, including carcass density and carcass size class. We detected no competing models (ΔAICc value <2). Detection rates by ground surveyors were lower in low carcass density plots than high density plots, but the relationship was weak ($p = 0.7$) (Figure 1A). Meanwhile, detection rates by ground surveyors were also lower for small birds ($p < 0.0001$) and bats ($p <0.0001$) than large birds (Figure 1B).

Detection by the CNN was best explained by the global model, including carcass density, size class, ground cover, and VOR. We detected no competing models (ΔAICc value <2). Similar to ground surveyors, CNN detection rates decreased in low carcass density plots, but the relationship was weak ($p = 0.7$) (Figure 2A). CNN detection rates had a strong negative association with both cropland ($p < 0.05$) and pasture ($p < 0.0001$) ground covers compared to dirt/gravel (Figure 2B). Additionally, detection rates were also lower for both small birds ($p < 0.0001$) and bats ($p < 0.0001$) than large birds (Figure 2C). Finally, CNN detection rates decreased as VOR increased ($p < 0.001$) (Figure 2D).

DISCUSSION

We evaluated detection rates of a convolutional neural network trained to detect bird and bat fatalities with ground surveyors for implementation in post-construction mortality monitoring. While the initial testing performed on the trained CNN was highly successful both in detection and classification scenarios (Chapter II and Chapter III), when presented with a new set of imagery that varied in both species and ground cover, the CNN did not perform as well. The ground surveyors performed similarly to those engaged in actual PCM searches (Barrientos et al. 2018), and as such, we believe their detection rates to have been representative of a realistic scenario.

The degree to which the CNN failed to detect bird and bat carcasses was surprising, but leaves room for further development. The ground covers and carcasses selected for this study had twofold purposes: 1) to test the CNN on species and ground covers that were both familiar (i.e., some species and plots were what the CNN had previously been trained on in Chapter I), and 2) to provide additional novel data to continue training the CNN on for further generalization. While the CNN would be likely to encounter new species and ground covers in real-life implementation, the novelty of some of these species and locations may have caused additional confusion for the CNN, leading to lower detection rates. The CNN was originally trained on 55 species, and tested on 52 species in this study. Of these, 38 species overlapped and 30 did not. However, average detection rates comparing trained and novel species were not greatly different (26.89% versus 33.92%, respectively), but this study would benefit from future, more focused research on this topic. We recommend that future studies perform several iterations of validation and follow-up training until satisfactory detection rates have been achieved on novel image sets. While this study's results have indicated that this method is not yet ready for implementation, the initial testing of both object detection and classification (Chapters 1and 2) show promise for this method with further training. Future studies examining the success of machine learning algorithms in place of alternative methods for ecological monitoring should not assume that initial validation can be considered applicable to new image sets with similar, but novel environments and objects. Furthermore, there is a need to expand sensor-platform combinations such that the CNN can handle different technological developments.

Recent studies have found success detecting bird and bat collisions using stationary multi-spectral visual-near infrared cameras mounted to the nacelle of wind turbines (Happ et al. 2021), which suggests that further exploration into alternative cameras or filter lenses may improve detection and additionally weed out high false positive rates displayed by the trained CNN in Chapter II. While RGB cameras and fixed-wing platforms have been shown effective for larger wildlife in homogenous, minimally vegetated habitats, more complex scenarios including smaller wildlife, habitats with denser vegetation and more complex topography have required the use of multispectral sensors and multirotor platforms for success (Corcoran et al. 2021).

Ecological image datasets can be highly complex, particularly when concerning small, camouflaged targets, diverse carcass orientations, vegetative obstruction, vegetation colors and shapes, in addition to more common challenges of reflection and image blur. While the combination of a UAS and machine learning algorithm has strong potential for future successful deployment in post-construction monitoring, significant additional training is needed to meet or exceed other proven survey methods. Finally, while the combination of a UAS and machine learning does have the potential to standardize data collection methods further, this method is prone to similar downfalls that both ground surveyors and detection dogs experience, such as decreased detection rate with increasingly obstructive vegetation and smaller species. As such, care must be given when selecting an appropriate survey method for the proposed study as one size may not fit all.

LITERATURE CITED

Arnett, E. B. 2006. A preliminary evaluation on the use of dogs to recover bat fatalities at wind energy facilities. Wildlife Society Bulletin 34(5):1440-1445.

Barrientos, R., Martins, R. C., Ascensão, F., D'Amico, M., Moreira, F., & Borda-de-Àgua, L. (2018). A review of searcher efficiency and carcass persistence in infrastructure-driven mortality assessment studies. *Biological Conservation 222*:146-153.

Barros, M. A. S., L. Iannuzzi, I. Leite de Holanda Silva, A. Otálora-Ardila, and E. Bernard. Factors affecting searcher efficiency and scavenger removal of bat carcasses in Neotropical wind facilities. Journal of Wildlife Management 86(4): e22198.

Corcoran, E., M. Winsen, A. Sudholz, and G. Hamilton. 2021. Automated detection of wildlife using drones: synthesis, opportunities, and constraints. Methods in Ecology and Evolution 12:1103-1114.

Floreano, D. and R. Wood. 2015. Science, technology and the future of small autonomous drones. Nature 521(7553): 460–466.

Happ, C., A. Sutor, and K. Hochradel. 2021. Methodology for automated visual detection of bird and bat collision fatalities at onshore wind turbines. Journal of Imaging 7(272): 25 pp.

Koh, L. P. & Wich, S. A. (2012). Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. *Tropical Conservation Science 5(2):*121-132. https://doi.org/10.1177/194008291200500202

Linchant, J., Lisein, J., Ngabinzeke, J. S., & Lejeune, P. (2015). Are unmanned aircraft (UAS) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Review 45(4)*: 239-252. https://doi.org/10.1111/mam.12046.

Mathews, F., M. Swindells, R. Goodhead, T. A. August, P. Hardman, D. M. Linton, and D. J. Hosken. 2013. Effectiveness of search dogs compared with human observers in locating bat carcasses at wind-turbine sites: a blind randomized trial. Wildlife Society Bulletin 37(1):34-40.

Mazerolle, M. J. (2022) AICcmodavg: model selection and multimodel inference based on (Q)AIC(c). R package version 2.3-1. <https://cran.r-project.org/package=AICcmodavg>.

North American Breeding Bird Survey [NABBS]. (2020). Weather Codes. Laurel, MD, USA: U.S. Geological Survey Patuxent Wildlife Research Center. <http://www.pwrc.usgs.gov/BBS/participate/training/appendixA.html>.

Poysa, H., J. Kotilainen, V. Vaananen, and M. Kunnasranta. 2018. Estimating production in ducks: a comparison between ground surveys and unmanned aircraft surveys. European Journal of Wildlife Research 64(74).

Ransom, J. I. 2012. Detection probability in aerial surveys of feral horses. Journal of Wildlife Management 76(2):299-307.

Reyes, G. A., Rodriguez, M. J., Lindke, K. T., Ayres, K. L., Halterman, M. D., Boroski, B. B., & Johnston, D. S. (2016). Searcher efficiency and survey coverage affect precision of fatality estimates. *Journal of Wildlife Management 80(8)*:1488-1496. https://doi.org/10.1002/jwmg.21126.

Robel, R. J., J. N. Briggs, A. D. Dayton, and L. C. Hulbert. 1970. Relationships between visual obstruction measurements and weight of grassland vegetation. Journal of Rangeland Management 23(4):295-297.

Rosa, I. M. D., Marques, A.T., Palminha, G., Costa, H., Mascarenhas, M., Fonseca, C., & Bernardino, J. (2016). Classification success of six machine learning algorithms in radar ornithology. *Ibis 158*: 28–42. https://doi.org/10.1111/ibi.12333.

U.S. Environmental Protection Agency [USEPA]. 2013. Primary distinguishing characteristics of level III ecoregions of the continental United States. Available online: https://www.epa.gov/eco-research/ecoregions-north-america#:~:text=Level%20III%20mapping%20describes%20smaller,as%20well%20as%20decision%2Dmaking.

U.S. Fish and Wildlife Service [USFWS]. 2012. U.S. Fish and Wildlife Service land-based wind energy guidelines. U.S. Fish and Wildlife Service, Washington, D.C. 82 pp.

Wargo, C.A., Church, G.C., Glaneueski, J., & Strout, M. (2014). Unmanned aircraft systems (UAS) research and future analysis. *2014 IEEE Aerospace Conference*, *Big Sky, MT, USA.*

FIGURES

Figure 1. Detection rates with 95% confidence intervals of a ground surveyor searching for bird and bat carcasses.

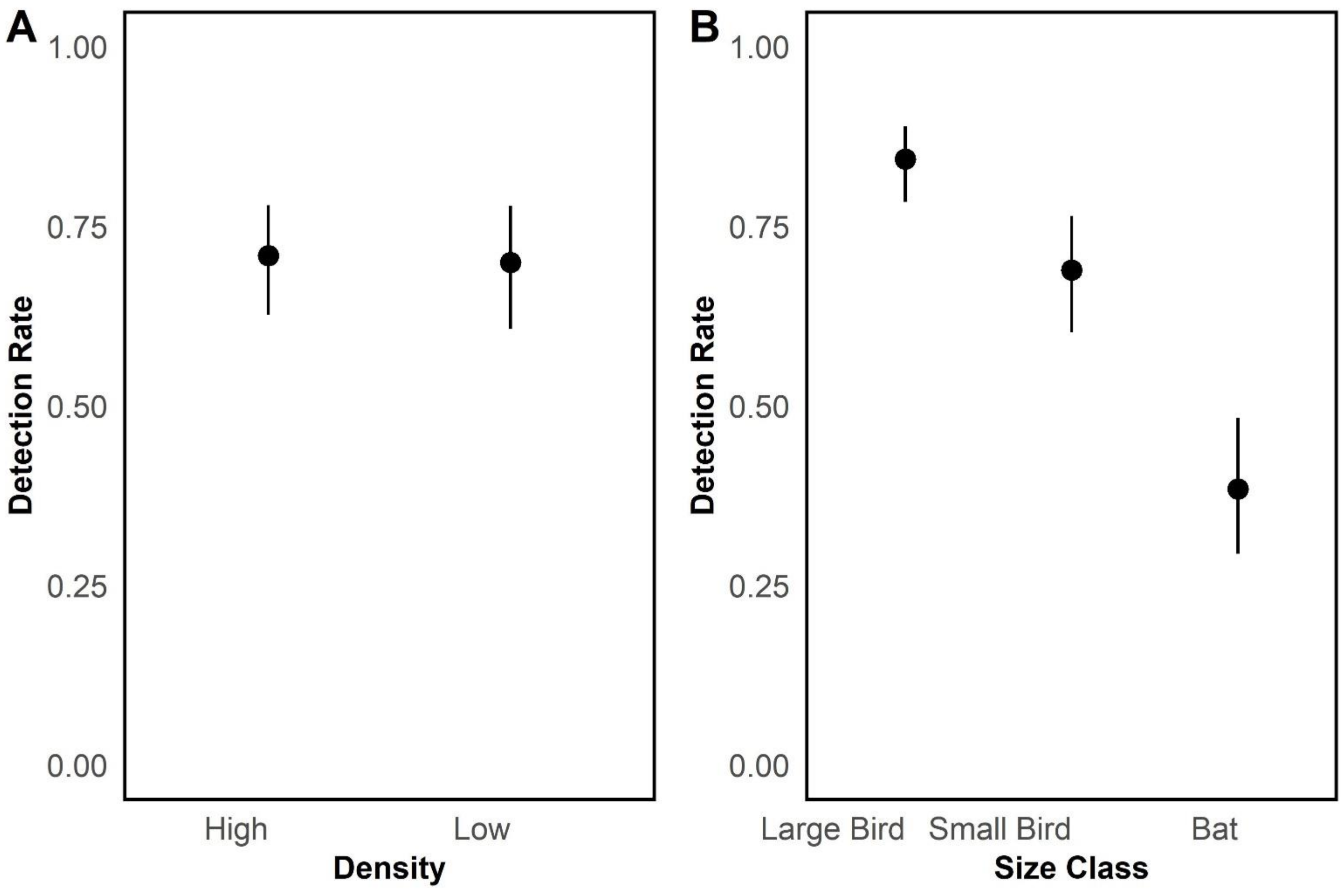
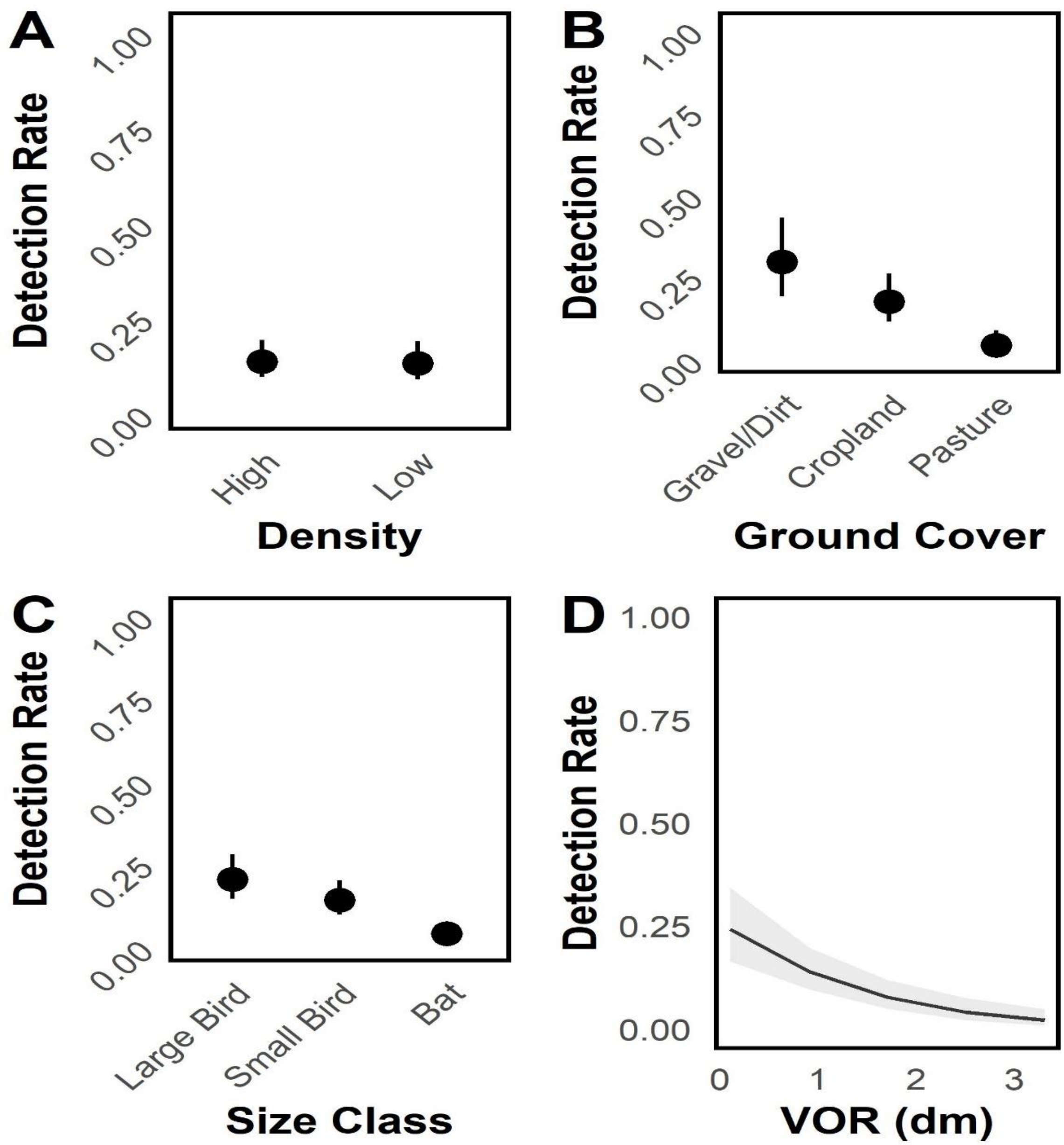


Figure 2. Detection rates with 95% confidence intervals of a convolutional neural network trained to detect bird and bat carcasses from uncrewed aircraft system imagery.



CHAPTER V COMPARING UNCREWED AERIAL SYSTEM AND TRADITIONAL GROUND COUNTING METHODS OF BREEDING DUCK PAIRS

ABSTRACT Waterfowl population management is largely influenced by data collected during the breeding season, including pair surveys performed in the spring when ducks arrive in the Prairie Pothole Region of North America. Traditionally, counts of these pairs are performed both on the ground and in crewed aircraft during the Waterfowl Breeding Population and Habitat Survey and the Four-Square Mile Survey. Detection biases from ground observers can lead to reduced data quality and resulting population estimates used to inform state and federal regulations. Uncrewed aerial systems (UAS) have been increasingly incorporated into wildlife surveys due to their quick, repeatable data collection and ability to access difficult environments. Recent research has found that manual image review of UAS collected data has led to similar or higher counts when compared to ground surveying methods, but most of this research has been focused on duck broods or waterbird colonies. We compared total counts of ducks in spring ponds in North Dakota, USA between manual UAS image review and traditional ground surveys. We conducted 47 flights with paired ground surveys at 45 ponds between 24 April and 27 May 2020 and used a generalized linear mixed model to determine differences in count methods. Ultimately, we found that UAS image review yielded higher duck counts than ground surveys ($p < 0.0001$), but further research is needed to examine detection biases in manual image reviewers.

KEY WORDS UAS, duck, pair survey, survey method, UAS, waterfowl

INTRODUCTION

Timely, accurate monitoring methods are instrumental to the management of wildlife across taxa for determining population status, range changes, behavior, and more, ultimately informing state, federal, and international regulations such as the Endangered Species Act, Migratory Bird Treaty

Act, and National Environmental Policy Act. Traditional monitoring methods typically rely on ground-based surveyors, such as distance sampling deer (LaRue et al. 2007), carnivore scat surveys and hair-snags (Phoebus et al. 2020), mark-recapture used widely for a variety of taxa, including marine mammals (Hammond et al. 2021), track surveys for otters and other wildlife (Evans 2006), and more. Despite the long-standing use of these methods and other wildlife surveying techniques, common challenges across all these surveys include cost, visibility, detection, observer biases, misidentification, and lack of standardization in protocols (Evans 2006, Corace et al. 2018, Hammond et al. 2021).

The management of duck populations requires precise breeding pair count data in the spring to predict reproductive potential for each species. These data, along with information about environmental conditions, are used to monitor population trends, inform annual harvest regulations, determine conservation priorities, and guide management, research, and funding decisions (Blohm et al. 2006). Within the Prairie Pothole Region (PPR), where over 50% of North America's ducks are produced (Bellrose 1980, Batt et al. 1989), two main surveys have been used to supply breeding duck pair count information: the Waterfowl Breeding Population and Habitat Survey (WBPHS; Smith 1995) and the Four-Square Mile Survey (FSMS; Reynolds et al. 2006). During the WBPHS, biologists in crewed aircraft fly established transects within 50 strata counting duck pairs and lone ducks within wetlands across Canada and the northern plains of the United States (Smith 1995, USFWS 2022). To account for visibility bias, observers on the ground count ducks in all ponds within each transect in a stratum. Similarly, the FSMS consists of point counts within a sample of wetlands throughout the United States portion of the PPR to be surveyed from the ground twice within May and early June. Unlike the WBPHS, the FSMS does not account for visibility bias and assumes observers can detect all pairs present on survey wetlands (Dzubin 1969, Hammond 1969).

Despite their longstanding use, similar to other traditional ground survey methods, the ground observer methods utilized by WBPHS and FSMS are not without weaknesses. Inconsistencies in field personnel experience, incomplete detection, double counting of birds, and disturbance have all been cited as tradeoffs with ground observers during these surveys (Dzubin 1969, Smith 1995) and during other surveys that have used similar methods (Götmark 1992, Thompson 2002, Boback et al. 2020). Double counting and incomplete detection of birds could bias counts, inflating or underestimating true abundance, respectively, whereas varying field personnel experience and disturbance have additional data and ecological concerns, such as misidentifying species, miscounting individuals or introducing further bias to counts, and possibly impacting fitness. Further, environmental variables such as vegetative obstruction, wetland size, and inclement weather make detection even more challenging and increase detection bias (Dzubin 1969, Pagano et al. 2014).

In response to the challenges presented by ground observer techniques for surveys like WBPHS and the FSMS, a growing number of studies have started to investigate the utility of uncrewed aerial systems (UAS) as a potential solution or improvement over ground surveys (Pöysä et al. 2018, Bushaw et al. 2020, Ryckman et al. 2022). UAS offer rapid data collection that is repeatable, high coverage, and likely offer fewer visibility challenges due to the nadir position (90° angle) of the sensor (Koh & Wich 2012, Wargo et al. 2014, Hodgson et al. 2016), making commonly used hemi-marsh environments by spring arriving ducks (Murkin et al. 1997) more accessible. Image counts from an UAS have been found to provide higher ground counts for common teal broods (*Anas crecca*: Poysa et al. 2018) and still other studies have indicated substantially higher detection rates with the use of UAS in brood surveys (Bushaw et al. 2021). However, while initial research on pair avoidance behavior has shown mild behavior changes (Ryckman et al. 2022), we are not aware of empirical studies investigating UAS's utility for supplementing or replacing ground observers in pair surveys.

Given the current gap in empirical data regarding the use of UAS in waterfowl pair surveys, the importance of detection in these surveys, and the international significance of these surveys to waterfowl management, an investigation of possible improvements to methodology through the use of UAS for counting breeding duck pairs is merited. Before standardized implementation of UAS can occur, proof of concept studies should be performed to determine if the use of UAS for counting breeding duck pairs performs better, or at least the same, than currently utilized human ground observers. We hypothesized that total duck count from UAS and ground surveyors would be similar, and that wetland size might additionally explain variation in the data with counts performed by UAS increasing with increasing wetland size, while counts with ground surveyors would decrease due to likely inability to see into larger wetlands. As such, we aim to compare duck counts taken using traditional ground observer methods with those manually counted from UAS imagery.

STUDY AREA

We conducted breeding pair duck surveys in the Missouri Coteau region of North Dakota. The Missouri Coteau region totals 7.3 million ha of the greater Prairie Pothole Region and is defined by its hills and plentiful glacial basins that range from ephemeral to permanent status (Stewart and Kantrud 1973, Phillips et al. 2005). Within North Dakota, our study focused specifically on the two adjacent ranches - Ducks Unlimited Coteau Ranch (1,214 ha) and The Nature

Conservancy's Davis Ranch (2,931 ha) within Sheridan County (centroid: 47.383336°N, 100.278731°W; Figure 1).

METHODS

Field methods Between 24 April and 27 May 2020, we performed 47 paired UAS and ground observer counts of breeding duck pairs in 45 wetlands in North Dakota. An additional flight at two wetlands was performed within 24 hours of the first to collect additional imagery of ducks. We selected these 45 predominantly seasonal wetlands as they were consistently used by ducks throughout the study period. We collected survey data specifically on blue-winged teal (*Spatula discors*), mallards (*Anas platyrhynchos*), gadwall (*Mareca strepera*), northern pintails (*Anas acuta*), northern shovelers (*Spatula clypeata*), American wigeon (*Mareca americana*), American green-winged teal (*Anas carolinensis*), redheads (*Aythya americana*), lesser scaup (*Aythya affinis*), canvasback (*Aythya valisineria*), ruddy ducks (*Oxyura jamaicensis*), and buffleheads (*Bucephala albeola*) due to their prevalence in the immediate area. Single observers located the best vantage point for viewing the entire wetland and minimizing disturbance, setting up 30 minutes prior to the UAS flight. If the wetland was too large for both the observer and UAS to cover in a single flight, a portion of it was predetermined as the surveyed area, and the observer would count ducks only within that section where the UAS flew. Ground observers synchronized their count survey with the UAS survey through text message communication with the flight operator, recording species and counting pairs and lone males and females with binoculars throughout the duration of the UAS flight. Ground observers documented if a duck flew or swam out of the survey area, noting species, sex, and count. Survey times were documented, along with a predetermined wetland identifier and wetland cover type following USFWS FSMS Protocols (USFWS 2010).

We conducted UAS flights with a DJI Matrice 200 V2 quadcopter (color: black, weight: 4.53 kg, operating temp: -20°C to 40°C) with a Zenmuse X5S (RGB) sensor and attached Olympus 45 mm lens. We flew the UAS at 45 m above ground level, allowing for a ground sampling distance of approximately 0.44 cm per pixel. We performed preprogrammed lawn-mower grid transects (DJI Pilot version 1.8.0) that ran parallel to the ducks on the wetland to minimize disturbance (McEvoy et al. 2016) at 5 m/s and 60% overlap. Additional methodological details can be found in Ryckman et al. (2022). We obtained permissions from the North Dakota Game and Fish Department (GNF04912726, GNF05182785), UND Institutional Animal Care Use Committee A3917-01, Protocol #1904–2, and the UND Unmanned Aircraft Systems Research Compliance Committee Approval (Approved April 12, 2019).

Image review

A biological technician from the University of North Dakota reviewed collected imagery within an in-house customed open-source annotation tool (Lin 2015). This tool allowed the reviewer to zoom as needed, draw bounding boxes, and make species or taxon-identifying annotations within the image (Figure 2). The technician scanned each image in a lawn-mower grid fashion, counting ducks and identifying them to species when possible. If the technician was not strongly confident in their species identification, they labeled the duck as “other duck”. The technician attempted to keep track of birds as they moved across imagery, aided by the 60% overlap of imagery, to minimize the likelihood of double counting birds. A second reviewer, a trained biologist with a background in waterfowl, reviewed the annotations created by the first to confirm species identification. If the biologist disagreed with the technician’s assessment, the species identification was deferred to the biologists’ assessment.

Data analysis

We used a generalized linear mixed model with a Poisson distribution to test if there was a difference in counts performed by ground observers compared to those manually counted from UAS imagery. We implemented package lme4 (Bates et al. 2015) in R version 1.4.1106 to build three models, one relating total duck count to survey method interacting with wetland size (ha), assuming size may play a role in detection (Dzubin 1969, Pagano et al. 2014), a second solely relating total duck count to survey method, and a null model. We incorporated wetland identifier as a random effect in all models. We calculated wetland size (ha) from National Wetlands Inventory data (USFWS 2018) for each wetland. We used package AICcmodavg (Mazerolle, 2020) to implement Akaike's Information Criterion model selection adjusted for small sample sizes (AICc) to determine if wetland size helped describe total duck count.

RESULTS

Our paired survey at 45 wetlands (mean = 1.17 ha, range = 0.02 – 16.16 ha) resulted in the ground observer counting a total of 581 ducks, while UAS image reviewing recorded 801 ducks. Image review of 36,471 total images took approximately 326.25 hours (0.01 hours/image). The technician reviewing imagery missed detecting all ducks in three wetlands, resulting in missed counts of 13 total ducks detected by ground surveyors. Mallards, gadwall, northern pintail, northern shoveler, American wigeon, American green-winged teal, lesser scaup, canvasback, redheads, and ruddy ducks were all detected in surveys, and no buffleheads were encountered. Ground observers were able to identify all ducks to species, while the technician reviewing imagery was unable to identify 381 (51%) of 749 ducks. The biologist reviewing imagery counted and identified additional birds but was still unable to identify 346 (43%) of 801 ducks due to image blur, reflection/glare causing washout, and a general lack of context clues.

Through AICc model selection, we determined that the top model was total count predicted by survey method (fixed effect) with wetland identifier (random effect) (Table 1). We detected no competing models (ΔAICc value <2). We found survey method had a strong association with total count ($ß= 0.32$, $SE = 00.5$, $p < 0.0001$) and that UAS image reviewers counted 10 ducks to every 7 that ground observers detected (Figure 3).

DISCUSSION

As it stands, manual UAS image review may provide similar or better counts to ground surveys, but detection biases and time considerations must be evaluated prior to implementation. While counts from imagery may reduce biases from observers such as some visibility issues, terrain, and more (Dulava et al. 2015), they may also introduce new bias that must be considered when interpreting data. While the image reviewer in our study was instructed to keep track of previously counted ducks when scanning imagery, it is possible that some ducks were still double counted. Barr et al. (2018) found that UAS image reviewers occasionally overcounted or falsely counted waterbirds. Use of video may allow reviewers to keep better track of ducks as the UAS moves over the wetland, and may also provide extra context, such as flushes, arrivals, and species identification clues, that may not be visible in still imagery (Dulava et al. 2015). Further, Ryckman et al. (2022) found that ducks often moved away from the sound of UAS, which may contribute to double counting of individuals. Despite this, the nadir position of the sensor (i.e., sensor pointed directly down at 90 degree position from ground) on the UAS also may allow better viewing of ducks in wetlands with extensive vegetative cover that may not be visible to ground observers (Pagano et al. 2014), which could also explain higher counts of ducks in imagery. However, the nadir position may create increased challenges with glare, resulting in difficulty identifying to species, but this may be improved by adjusting the camera angle (Hodgson et al. 2013).

We hypothesized that wetland size would play a role in counts; however, unlike previous studies (Pagano and Arnold 2009), wetland size did not influence total counts by either survey method. This lack of effect could have been due to the low variation in wetland size across our sample as only two wetlands were greater than 3.22 ha, which would have resulted in fewer issues for ground surveyors' visibility across wetlands. Wetland size along with height and density of vegetative cover likely interact posing detection biases of varying degrees due to visibility; however, we were unable to incorporate vegetation characteristics into our study.

Additional biases likely impacted both the counting and species identification in our study. While our study was not specifically looking at species identification, our image reviewer was unable to confidently identify approximately half of the observed ducks. The difficulties with species identification are likely a result of a variety of factors, including reviewer quantity and experience, overhead vegetative obstruction (Barr et al. 2018), image quality from blur or reflectance (Chabot et al. 2015), and a lack of species characteristic context, such as speculum visibility, that ground observers are likely to view from bird movement. Barr et al. (2018) found that overhead vegetation, lighting conditions, and species coloration may lead to biases in counting by image reviewers. As such, time of day should be considered when designing surveys as there may be optimal times to reduce glare, improving species identification conditions. Additionally, more research is needed to determine image reviewer detection biases as this is likely to impact not only detection, but successful species identification. Further, image reviewers are likely to have different biases than traditional ground observers where most previous research has focused.

Perhaps most importantly, it should be noted that post-survey image review was a time exhaustive practice and defeated any time saved through remote image collection. Time-saving automation efforts for avian studies are well underway and may reduce image review time to 5–10% of that of manual review (Chabot and Francis 2016, Chabot et al. 2018). However, challenges still exist with automation, including environmental variables (weather conditions, reflectance, shadows), sensor resolution, target disposition and size, and false positives (Chabot et al. 2015, Chabot and Francis 2016, Zhou et al. 2021). Improving automation methods still rely substantially on manual review to identify ducks to be able to accurately train these classification methods and thus, it is important to understand bias and challenges in this manual review process. In addition to temporal efficiency, feasibility of flight operations needs to be weighed in large wetlands where battery life may not be sufficient and UAS may need to go beyond visual line of sight, which is currently prohibited in the United States under the Federal Aviation Administration's Part 107 without a waiver (Floreano and Wood 2015). Exceptions to this rule may be provided with a waiver and may depend upon where operations occur.

At this time, manual image review of UAS may not be the most efficient route for surveying breeding duck pairs. However, rapid research in automation may facilitate the practicality of implementing UAS in breeding duck pair surveys, but regulatory and operational hurdles must still be factored in. While further research is needed to determine image reviewer detection biases and challenges in species identification from remotely sensed imagery, increased counts from this method compared to traditional ground surveys shows promise in utilizing UAS for breeding duck pair surveys in the future.

ACKNOWLEDGMENTS

Funding for our project was provided by Ducks Unlimited, Inc. (SNE) and the North Dakota Department of Commerce Research ND Award (Grant #: 19-11-G-229; SNE), University of North Dakota (UND) College of Arts and Sciences State Needs Award (SNE), the UND Biology Department's Game Management Scholarship (MDR), UND Dissertation Completion Fellowship. We thank Mason Sieges and a multitude of technicians for their assistance in data collection and flight operations. SE, MR, CF and SY designed the study; MR supervised data collection in the field; SY supervised image data collection; AJ performed image data collection; SY analyzed the data and wrote the manuscript with edits from SF, MR, CF, KK, and AJ.

LITERATURE CITED

Barnas, A., R. Newman, C. J. Felege, M. P. Corcoran, S. D. Hervey, T. J. Stechmann, R. F. Rockwell, and S. N. Ellis-Felege. 2017. Evaluating behavioral responses of nesting lesser snow geese to unmanned aircraft surveys. Ecology and Evolution 8:1328–1338.

Barr, J. R., M. C. Green, S. J. DeMaso, and T. B. Hardy. 2018. Detectability and visibility biases associated with using a consumer-grade unmanned aircraft to survey nesting colonial waterbirds. Journal of Field Ornithology 89(3):242-257.

Bates D., M. Mächler, B. Bolker, and S. Walker. 2015. Fitting linear mixed-effects models using lme4." *Journal of Statistical Software* 67(1): 1–48.

Batt, B. D. J., M. G. Anderson, C. D. Anderson, and F. D. Caswell. 1989. The use of prairie potholes by North American ducks. Pages 204–227 *in* A. van der Valk, editor. Northern prairie wetlands. Iowa State University Press, Ames, USA.

Bellrose, F. C. 1980. Ducks, geese, and swans of North America. Second Edition. Stackpole Books, Harrisburg, Pennsylvania, USA.

Blohm, R. J., D. E. Sharp, P. I. Padding, R. W. Kokel, and K. D. Richkus. 2006. Integrated waterfowl management in North America. Waterbirds around the world. Eds. G. C. Boere, C. A. Galbraith, and D. A. Stroud. The Stationary Office, Edinburgh, UK. pp. 199–203.

Boback, S. M., M. G. Nafus, A. A. Yackel Adams, and R. N. Reed. 2020. Use of visual surveys and radiotelemetry reveals sources of detection bias for a cryptic snake at low densities. Ecosphere 11(1):e03000. 10.1002/ecs2.3000.

Bushaw, J. D., K. M. Ringelman, M. K. Johnson, T. Rohrer, and F. C. Rohwer. 2020. Applications of an unmanned aerial vehicle and thermal-imaging camera to study ducks nesting over water. Journal of Field Ornithology 91(4):409–420.

Bushaw, J. D., C. V. Terry, K. M. Ringelman, M. K. Johnson, K. M. Kemink, and F. C. Rohwer. 2021. Application of unmanned aerial vehicles and thermal imaging cameras to conduct duck brood surveys. Wildlife Society Bulletin 45(2):274–281.

Chabot, D., S. R. Craik, and D. M. Bird. 2015. Population census of a large common tern colony with a small unmanned aircraft. PLoS ONE 10(4):e0122588.

Chabot, D., and C. M. Francis. 2016. Computer-automated bird detection and counts in high-resolution aerial images: a review. Journal of Field Ornithology 87(4):343–359.

Chabot, D., C. Dillon, and C. M. Francis. 2018. An approach for using off-the-shel object-based image analysis software to detect and count birds in large volumes of aerial imagery. Avian Conservation and Ecology 13(1):15.

Corace R. G. III, S. A. Weiss, and L. M. Shartell. 2018. Volunteer observer bias and sharp-tailed grouse lek counts in the Upper Midwest. Journal of Fish and Wildlife Management 9(2):666–677; e1944-687X. https://doi.org/10.3996/112017-JFWM-095

Dulava, S., W. T. Bean, O. M. W. Richmond. 2015. Applications of unmanned aircraft systems (UAS) for waterbird surveys. Environmental Reviews and Case Studies 17(3): 201–210.

Dzubin, A. 1969. Assessing breeding populations of ducks by ground counts (pp. 178–230). Jamestown: Northern Prairie Research Center.

Ellis-Felege, S. N., T. Stechmann, S. Hervey, C. J. Felege, R. F. Rockwell, and A. F. Barnas. 2022. Nesting common eiders (*Somateria mollissima*) show little behavioral response to fixed-wing drone surveys. Drone Systems and Applications 10(1):1–14.

Evans, J.W. 2007. Observer error in identifying species using indirect signs: analysis of a river otter track survey technique. Doctoral dissertation, Texas A&M University.

Floreano, D., and R. J. Wood. 2015. Science, technology and the future of small autonomous drones. Nature 521(7553):460-466.

Götmark, F. 1992 The effects of investigator disturbance on nesting birds. Current Ornithology: 63–104.

Hammond, M. C. 1969. Notes on conducting waterfowl breeding population surveys in the north central states. Pages 238-254 *in* Saskatoon Wetlands Seminar. Canadian Wildlife Service Report Ser. 6.

Hammond, P.S., T.B. Francis, D. Heinemann, K.J. Long, J.E. Moore, A.E. Punt, R.R. Reeves, M. Sepúlveda, G.M. Sigurðsson, M.C. Siple and G. Víkingsson. 2021. Estimating the abundance of marine mammal populations. Frontiers in Marine Science(8).Hodgson, A., N. Kelly, and D. Peel. 2013. Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. PLoS one 8(11): e79556.

Hodgson, J. C., S. M. Baylis, R. Mott, A. Herrod, and R. H. Clarke. 2016. Precision wildlife monitoring using unmanned aerial vehicles. Scientific Reports 6:22574.

Koh, L. P. & Wich, S. A. 2012. Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. Tropical Conservation Science 5(2):121–132. https://doi.org/10.1177/194008291200500202

LaRue, M. A., Nielsen, C. K., & Grund, M. D. 2007. Using distance sampling to estimate densities of white-tailed deer in south-central Minnesota. The Prairie Naturalist 39(2).

Lenth, R. V. 2021. Emmeans: estimated marginal means, aka least-squares means. R package version 1.6.1. <https://CRAN.R-project.org/package=emmeans>.

Lin, Tzuta. 2015. LabelImg. GitHub Repository <https://github.com/tzutalin/labelImg>.

Marc J. Mazerolle (2020) AICcmodavg: Model selection and multimodel inference based on (Q) AIC(c). R package version 2.3-1.< https://cran.r-project.org/package=AICcmodavg>.

Murkin, H. R., E. J. Murkin, and J. P. Ball. 1997. Avian habitat selection and prairie wetland dynamics: a 10-year experiment. Ecological Applications 7(4):1144–1159.

Pagano, A. M., and T. W. Arnold. 2009. Detection probabilities for ground-based breeding waterfowl surveys. Journal of Wildlife Management 73(3):392–398.

Pagano, A. M., C. L. Amundson, M. R. Pieron, T. W. Arnold, and T. C. Kimmel. 2014. Using sightability-adjusted brood-pair ratios to estimate waterfowl productivity. Wildlife Society Bulletin 38(3):566–573.

Phillips, R. L., O. Beeri, and E. S. DeKeyser. 2005. Remote wetland assessment for Missouri Coteau prairie glacial basins. Wetlands 25(2):335–349.

Phoebus, I., J. Boulanger, H. G. Eiken, I. Fløystad, K. Graham, S. B. Hagen, A. Sorensen, and G. Stenhouse. 2020. Comparison of grizzly bear hair-snag and scat sampling along roads to inform wildlife population monitoring. Wildlife Biology (3):1-12.

Pöysä, H., J. Kotilainen, V-M. Väänänen, and M. Kunnasranta. 2018. Estimating production in ducks: a comparison between ground surveys and unmanned aircraft surveys. European Journal of Wildlife Research 64:74.

Reynolds, R. E., T. L. Shaffer, C. R. Loesch, and R. R. Cox, Jr. 2006. The Farm Bill and duck production in the Prairie Pothole Region: Increasing the benefits. Wildlife Society Bulletin 34:963–974.

Ryckman, M. D., K. Kemink, C. J. Felege, B. Darby, G. S. Vandeberg, and S. N. Ellis-Felege. 2022. Behavioral responses of blue-winged teal and northern shoveler to unmanned aerial vehicle surveys. PLoS ONE 17(1): e0262393.

Smith, G. W. 1995. A critical review of the aerial and ground surveys of breeding waterfowl in North America. Biological Science Report 5, National Biological Service, Washington, D. C. 252 pp.

Thompson, W. L. 2002. Towards reliable bird surveys: accounting for individuals present but not detected. The Auk 119(1):18–25.

U.S. Fish and Wildlife Service [USFWS]. 2020. Four Square Mile Survey Pair Count Instructions. U.S. Fish and Wildlife Service. <www.ecos.fws.gov>.

U.S. Fish and Wildlife Service [USFWS]. 2018. National Wetlands Inventory. U.S. Fish & Wildlife Service. < https://data.nal.usda.gov/dataset/national-wetlands-inventory>.

U.S. Fish and Wildlife Service [USFWS]. 2022. Waterfowl breeding population and habitat survey traditional survey. U.S. Fish and Wildlife Service Division of Migratory Birds. <www.migbirdapps.fws.gov>.

Wargo, C.A., Church, G.C., Glaneueski, J., & Strout, M. 2014. Unmanned aircraft systems (UAS) research and future analysis. 2014 IEEE Aerospace Conference, Big Sky, MT, USA.

Zhou, M., J. A. Elmore, S. Samiappan. K. O. Evans, M. B. Pfeiffer, B. F. Blackwell, and R. B. Iglay. 2021. Improving animal monitoring using small unmanned aircraft systems (sUAS) and deep learning networks. Sensors 21:5697.

TABLES & FIGURES

Table 1. Candidate list of generalized linear mixed models to evaluate how survey method (ground observer vs. uncrewed aerial system with manual image review) and wetland size relate to total duck counts during spring breeding pair surveys in Sheridan County, North Dakota, USA.

Model Name	Model Parameters	K	AIC	ΔAIC	Model Weight
Additive	Method + (1|wetland ID)	3	649.11	0.00	0.78
Interaction	Method * wetland size + (1|wetland ID)	5	651.58	2.47	0.22
Null	1 + (1|wetland ID)	2	682.15	33.04	0

Figure 1. Study area map of wetlands used for a surveying methodology comparison in April – May 2020 at the Ducks Unlimited, Inc's Coteau Ranch and The Nature Conservancy's Davis Ranch in Sheridan County, North Dakota, USA.

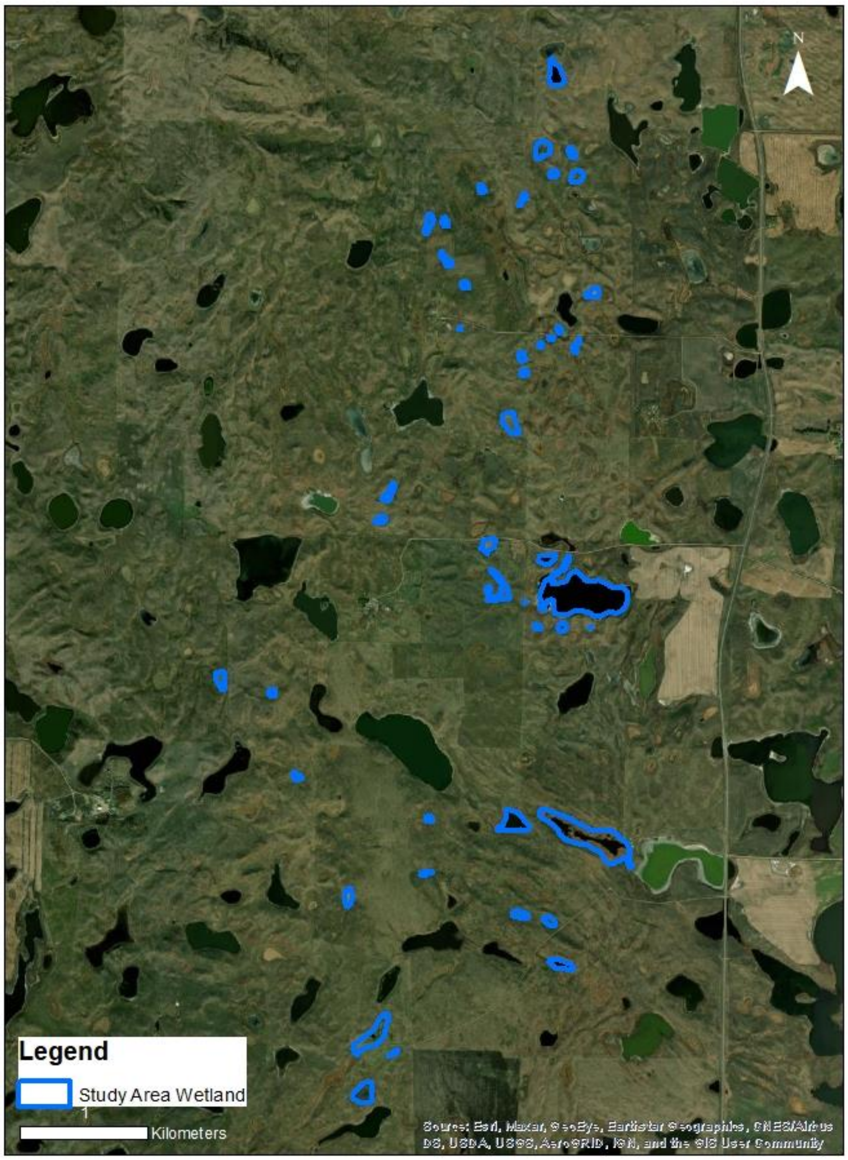


Figure 2. Open-source annotation tool used to detect and label ducks with their associated species name for UAS image review of breeding duck pairs collected April – May 2020 at the Ducks Unlimited, Inc's Coteau Ranch and The Nature Conservancy's Davis Ranch in Sheridan County, North Dakota, USA.

Figure 3. Predicted total counts of breeding ducks relative to survey method in paired ground and UAS breeding duck pair surveys at 45 wetlands performed April – May 2020 at the Ducks Unlimited, Inc's Coteau Ranch and The Nature Conservancy's Davis Ranch in Sheridan County, North Dakota, USA. Solid lines indicate 95% confidence intervals.

CHAPTER VI CONCLUDING THOUGHTS

Rapid advances in technology are driving the direction of most sectors, with the use of uncrewed aircraft systems (UAS) and machine learning becoming increasingly common for improving efficiency in all manners of the world. Within the field of wildlife biology, the two methods are being paired to bolster repeatability, amass large datasets at a fraction of the speed of normal techniques, improve accuracy, and navigate difficult to reach locations. Among the most common uses within wildlife are population surveys, whether that be long-standing methods such as the historic waterfowl breeding population survey or newer survey needs such as post-construction monitoring at energy projects. In our research, we developed and evaluated a new approach for monitoring at wind facilities that is promising for both pre- and post-construction surveys and poses implications for additional ecological surveys, such as waterfowl breeding pair surveys occurring annually in the northern United States and Canada.

In the first stage, we sought to amass an image library with labeled bird and bat carcasses to train and validate a convolutional neural network for post-construction monitoring at wind energy facilities. We collected imagery with a quadcopter flown below the rotor-swept area between the spring and fall of 2020 at both on-site wind energy facility locations and off-site areas that represented similar ground cover types that are common to wind energy facilities. We split the set of imagery into a training and validation set, and we trained two models using a RetinaNet that represented predominantly green and brown backgrounds. Due to extended spring and fall and drought conditions in North Dakota, the majority of the images were categorized within the brown model, and ultimately results from validation of the two models were combined. Detection of all carcasses was higher than currently used methods, including both human surveyors and detection dogs, with an accuracy of 98.7%. Due to low variability in the data, we were unable to determine additional factors impacting object detection such as climatic variability, sun angle, and carcass size. Despite the model's relative success in object detection of birds and bats, it output 536 false positives compared to the 302 true positive detections, which were primarily result of humans, shadows, snow, and vegetation within the imagery. Therefore, additional training imagery of potential false positives would enhance the use of the models in the future.

Using the same data set, we explored the same model's classification capabilities of bird and bat carcasses. Similar to its object detection, the model was highly successful at classifying the correct bird and bat species with overall 90.5% accuracy. To determine what best-informed species identification, we implemented generalized linear models and built three candidate models exploring sun angle, wind speed, sky cover, and species group. Through Akaike's Information Criterion (AICc) model selection, we determined that wind speed and sun angle best explained species identification of 51 bird species and five bat species. Lower wind speeds were associated with increased species identification accuracy (10 mph), and increased sun angle (morning and afternoon hours) improved species identification as well.

For the third stage of the process, we tested the trained CNN on a novel image data set and compared its object detection to currently accepted methods of ground surveyors in a simulated post-construction monitoring scenario. We performed near-simultaneous UAS and ground surveys with naive observers in plots with ground cover types commonly found on wind energy projects in spring through fall 2021. Bird and bat carcasses were placed in random locations throughout the plot, with location and numbers unknown to the ground surveyors. After collection, carcasses were labeled in the imagery for later detection confirmation, and the trained CNN was tested on the new image data set. Ultimately, the trained CNN performed poorly compared to prior validation in Chapter II and did not compete with the detection rate of the ground surveyors. Across 951 bird and bat carcasses, nine ground surveyors detected an average of 63.2%, while the trained CNN detected 28.9%. We further assessed the roles that factors such as vegetation structure, carcass density within the plot, and carcass size played in successful detection of the trained CNN and ground surveyors. Further, we wanted to know if surveyor experience played a role in the detection bird and bat carcasses. Only carcass size and carcass density in a plot informed ground surveyor detection, with carcass size being the most impactful. Ground surveyor detection rates decreased by decreasing size class, similarly to what was found by Barrientos et al. (2018). For the CNN, we found that detection was best explained by carcass density within the plot, carcass size class, ground cover type, and the visual obstruction reading of the vegetation. Similar to ground surveyors, detection decreased with decreasing carcass size, was lower in cropland and pasture than in dirt/gravel ground covers, and similarly, decreased with increasing visual vegetative obstruction.

Finally, we aimed to set the foundation for further exploration of the utility of UAS and manual detection of waterfowl compared to currently used ground surveyors. We conducted 47 flights with paired ground surveys at 45 ponds in the spring of 2020 and used generalized linear mixed models to assess differences in the two methods of counting. Image review yielded significantly higher duck counts than ground surveys, but biases such as overcounting, image blur, and bird movement may skew these results (Ryckman et al. 2022). Additionally, there is still additional efforts needed for species identification and the ability to automate pair survey data. Last, reflectance is another issue when working in wetland systems that make it more difficult for both manual and automated reviewers to detect and identify individuals.

While the CNN performed poorly in testing on the new data set, the initial stages of validation in object detection and classification hold great promise in the future of detecting and identifying bird and bat species in a post-construction monitoring scenario. Further training in new locations that present different vegetation structure and species, along with new sensor-platform combinations, is needed prior to implementing in actual post-construction monitoring, along with additional exploration into the causes and reduction of false positives. Some research has incorporated multi-spectral sensors with success at both detection and reduction of false positives in a post-construction monitoring scenario, and spectral research supports the idea that identification may be improved in imagery by means of either a near-infrared sensor or UV capable sensor (Happ et al. 2021, Helvey 2020). As such, future research should not only incorporate extensive model training, but explore the applications of multispectral sensors in the object detection and classification of both live and dead birds and bats in aerial imagery. Additionally, automation of waterfowl pair surveys has potential utility for both pre-construction monitoring at energy facilities, along with improving the efficiency and accuracy of historic surveys such as the Waterfowl Breeding Population Survey and Four-Square Mile Survey. Further exploration of image reviewer biases may help refine training datasets for improved validation results.

Many ecological surveys are rapidly transitioning from human observers to the automation of remotely captured imagery. While most efforts have focused on camera trapping or large mammals thus far (Lenzi et al. 2023, Vélez et al. 2023), our research has shown potential for its application on a multitude of bird and bat species ranging from small to large in a post-construction monitoring scenario but leaves room for improvement. While object detection of wildlife is largely the most important element of pre- and post-construction monitoring at wind energy facilities, species identification may lead to early warning triggers of potentially sensitive and covered species such as the Indiana bat (*Myotis sodalis*), northern long-eared bat (*Myotis septentrionalis*), or bald eagle (*Haliaeetus leucocephalus*). As such, additional construction and fine tuning of a CNN, and further exploration of image enhancement, may prove to be a useful and reliable tool for monitoring wildlife at energy facilities, with applications to additional sectors such as transportation that have potentially deleterious impacts on wildlife.

LITERATURE CITED

Barrientos, R., Martins, R. C., Ascensão, F., D'Amico, M., Moreira, F., & Borda-de-Àgua, L. (2018). A review of searcher efficiency and carcass persistence in infrastructure-driven mortality assessment studies. *Biological Conservation 222*:146-153. https://doi.org/10.1016/j.biocon.2018.04.014.

Happ, C., A. Sutor, and K. Hochradel. 2021. Methodology for the automated visual detection of bird and bat collision fatalities at onshore wind turbines. Journal of Imaging 7(272).

Helvey, M. W. 2020. Application of thermal and ultraviolet sensors in remote sensing of upland ducks. Thesis. Rochester Institute of Technology, Rochester, NY, USA.

Lenzi, J., A. F. Barnas, A.A. ElSaid, T. Desell, R. F. Rockwell, and S. N. Ellis-Felege. 2023. Artificial intelligence for automated detection of large mammals creates path to upscale drone surveys. Scientific Reports 13(947).

Ryckman, M. D., K. Kemink, C. J. Felege, B. Darby, G. S. Vandeberg, and S. N. Ellis-Felege. 2022. Behavioral responses of blue-winged teal and northern shoveler to unmanned aerial vehicle surveys. PLoS ONE 17(1): e0262393.

Vélez, J., W. McShea, H. Shamon, P. J. Castiblanco-Camacho, M. A. Tabak, C. Chalmers, P. Fergus, and J. Fieberg. 2022. An evaluation of platforms for processing camera-trap data using artificial intelligence. Methods in Ecology and Evolution 14(2):459-477.

APPENDIX A. Causes for false positives and corresponding classification and confidence levels outputs from a convolutional neural network trained to identify bird and bat carcasses for post-construction monitoring in landscapes common to North Dakota (i.e., cropland, pasture, dirt/gravel).

Cause of False Positive	CNN Classification Output	CNN Confidence Output
Cooler	Snowy Owl	90.75
Cooler	Snowy Owl	90.13
Cooler	Snowy Owl	84.23
Dirt	American Bittern	91.38
Dirt	American Bittern	88.03
Dirt	American Bittern	85.61
Dirt	American Bittern	82.51
Dirt	American Bittern	82.47
Dirt	American Bittern	81.27
Dirt	American Bittern	80.5
Dirt	Big Brown Bat	80.72
Dirt	Cedar Waxwing	92.27
Dirt	Cooper's Hawk	86.62
Dirt	European Starling	99.89
Dirt	European Starling	99.83
Dirt	European Starling	98.87
Dirt	European Starling	98.08
Dirt	European Starling	91.54

Dirt	European Starling	90.76
Dirt	European Starling	88.93
Dirt	European Starling	83.4
Dirt	European Starling	83.32
Dirt	European Starling	82.39
Dirt	European Starling	82.13
Dirt	Hoary Bat	93.57
Dirt	Hoary Bat	80.63
Dirt	Hoary Bat	80.22
Dirt	Mallard	91.59
Dirt	Peregrine Falcon	86.85
Dirt	Red-winged Blackbird	98.68
Dirt	Red-winged Blackbird	95.91
Dirt	Rock Pigeon	87.97
Dirt	Rock Pigeon	86.55
Dirt	Silver-haired Bat	89.36
Dirt	Silver-haired Bat	83.36
Dirt	Yellow-bellied Sapsucker	97.75
Dirt	Yellow-bellied Sapsucker	94.9
Dirt	Yellow-bellied Sapsucker	86.22
Dirt	Yellow-headed Blackbird	93.38
Fence	Ferruginous Hawk	99.1
Fence	Ferruginous Hawk	93.12

Fence	Ferruginous Hawk	83.11
Fence	Great Horned Owl	89.29
Fence	Great Horned Owl	82.94
Garbage	Black-crowned Night Heron	83.64
Garbage	Blue-winged Teal	80.68
Garbage	Gadwall	96.74
Garbage	Sharp-tailed Grouse	80.96
Garbage	Snowy Owl	98.94
Garbage	Snowy Owl	89.53
Glare	Pine Grosbeak	92.15
GPS	Garbage	95.98
GPS	Red-winged Blackbird	83.21
Helipad	European Starling	97.39
Helipad	Garbage	94.82
Helipad	Great Horned Owl	87.19
Helipad	Ring-necked Pheasant	92.93
Helipad	Ring-necked Pheasant	90.5
Helipad	Snowy Owl	98.25
Helipad	Snowy Owl	95.54
Helipad	Snowy Owl	89.81
Helipad	Snowy Owl	89.1
Helipad	Snowy Owl	87.58
Human	American Bittern	88.62

Human	American Bittern	94.3
Human	American Bittern	86.67
Human	Black-crowned Night Heron	97.95
Human	Black-crowned Night Heron	94.39
Human	Black-crowned Night Heron	93.07
Human	Black-crowned Night Heron	92.81
Human	Black-crowned Night Heron	91.09
Human	Black-crowned Night Heron	87.36
Human	Black-crowned Night Heron	85.94
Human	Black-crowned Night Heron	85.92
Human	Black-crowned Night Heron	85.9
Human	Black-crowned Night Heron	82.68
Human	Black-crowned Night Heron	81.62
Human	Black-crowned Night Heron	81
Human	Blue-winged Teal	96.38
Human	Blue-winged Teal	83.32
Human	Blue-winged teal	83.3
Human	Bufflehead	94.97
Human	Bufflehead	83.65
Human	Bufflehead	80.02
Human	European Starling	95.25
Human	European Starling	85.72
Human	Ferruginous Hawk	97.31

Human	Ferruginous Hawk	93.77
Human	Ferruginous Hawk	90.75
Human	Ferruginous Hawk	87.97
Human	Gadwall	98.88
Human	Gadwall	98.87
Human	Gadwall	97.99
Human	Gadwall	96.15
Human	Gadwall	96.11
Human	Gadwall	95.02
Human	Gadwall	94.91
Human	Gadwall	92.48
Human	Gadwall	92.12
Human	Gadwall	91.83
Human	Gadwall	91.48
Human	Gadwall	91.39
Human	Gadwall	90.05
Human	Gadwall	88.96
Human	Gadwall	88.41
Human	Gadwall	88.18
Human	Gadwall	88.05
Human	Gadwall	87.9
Human	Gadwall	87.56
Human	Gadwall	87.33

Human	Gadwall	85.67
Human	Gadwall	85.09
Human	Gadwall	84.82
Human	Gadwall	84.53
Human	Gadwall	83.05
Human	Gadwall	82.47
Human	Gadwall	82.33
Human	Garbage	99.95
Human	Garbage	99.37
Human	Garbage	98.79
Human	Garbage	98.15
Human	Garbage	97.49
Human	Garbage	97.04
Human	Garbage	95.46
Human	Garbage	95.18
Human	Garbage	94.18
Human	Garbage	93.91
Human	Garbage	93.1
Human	Garbage	93.07
Human	Garbage	92.64
Human	Garbage	91.77
Human	Garbage	90.23
Human	Garbage	90.02

Human	Garbage	89.68
Human	Garbage	89.04
Human	Garbage	87.14
Human	Garbage	86.49
Human	Garbage	84.93
Human	Garbage	84.88
Human	Garbage	83.22
Human	Garbage	83.07
Human	Garbage	82.55
Human	Garbage	82.38
Human	Garbage	82.25
Human	Garbage	80.52
Human	Garbage	78.21
Human	Herring Gull	95.85
Human	Mallard	99.94
Human	Mallard	99.7
Human	Mallard	99.46
Human	Mallard	99.01
Human	Mallard	99.01
Human	Mallard	98.98
Human	Mallard	98.86
Human	Mallard	98.83
Human	Mallard	97.9

Human	Mallard	97.66
Human	Mallard	97.47
Human	Mallard	97.47
Human	Mallard	97.29
Human	Mallard	96.25
Human	Mallard	95.83
Human	Mallard	95.8
Human	Mallard	95.59
Human	Mallard	95.13
Human	Mallard	94.26
Human	Mallard	94.06
Human	Mallard	93.95
Human	Mallard	93.71
Human	Mallard	93.15
Human	Mallard	93.05
Human	Mallard	92.67
Human	Mallard	92.33
Human	Mallard	92.22
Human	Mallard	91.82
Human	Mallard	91.18
Human	Mallard	90.75
Human	Mallard	90.61
Human	Mallard	90.29

Human	Mallard	90.13
Human	Mallard	90.11
Human	Mallard	89.96
Human	Mallard	89.84
Human	Mallard	89.75
Human	Mallard	89.58
Human	Mallard	89.08
Human	Mallard	88.91
Human	Mallard	88.75
Human	Mallard	88.4
Human	Mallard	86.67
Human	Mallard	86.33
Human	Mallard	86.21
Human	Mallard	86.07
Human	Mallard	85.77
Human	Mallard	85.56
Human	Mallard	85.01
Human	Mallard	85
Human	Mallard	84.86
Human	Mallard	84.22
Human	Mallard	83.94
Human	Mallard	83.41
Human	Mallard	83.28

Human	Mallard	83.2
Human	Mallard	83.14
Human	Mallard	82.9
Human	Mallard	82.36
Human	Mallard	82.17
Human	Mallard	81.74
Human	Ring-necked Pheasant	95.34
Human	Ring-necked Pheasant	87.18
Human	Ring-necked Pheasant	80.71
Human	Rock Pigeon	87.56
Human	Rock Pigeon	85.52
Human	Snowy Owl	99.96
Human	Snowy Owl	99.94
Human	Snowy Owl	99.61
Human	Snowy Owl	99.24
Human	Snowy Owl	98.26
Human	Snowy Owl	97.42
Human	Snowy Owl	96.17
Human	Snowy Owl	95.82
Human	Snowy Owl	95.72
Human	Snowy Owl	95.53
Human	Snowy Owl	95.5
Human	Snowy Owl	95.36

Human	Snowy Owl	95.17
Human	Snowy Owl	94.11
Human	Snowy Owl	93.76
Human	Snowy Owl	93.18
Human	Snowy Owl	92.63
Human	Snowy Owl	92.24
Human	Snowy Owl	91.74
Human	Snowy Owl	91.64
Human	Snowy Owl	91.16
Human	Snowy Owl	91.15
Human	Snowy Owl	89.32
Human	Snowy Owl	89.17
Human	Snowy Owl	89.14
Human	Snowy Owl	88.86
Human	Snowy Owl	87.48
Human	Snowy Owl	86.88
Human	Snowy Owl	86.51
Human	Snowy Owl	85.44
Human	Snowy Owl	84.74
Human	Snowy Owl	84.22
Human	Snowy Owl	83.39
Human	Snowy Owl	83.28
Human	Snowy Owl	82.37

Human	Snowy Owl	81.83
Human	Snowy Owl	81.1
Human	Snowy Owl	80.03
Ice	Ferruginous Hawk	98.14
Ice	Ferruginous Hawk	92.51
Ice	Ferruginous Hawk	83.96
Ice	Hoary Bat	83.19
Ice	Hoary Bat	81.67
Ice	Snowy Owl	86.8
Landscaping Cloth	Great Horned Owl	99.22
Landscaping Cloth	Great Horned Owl	96.93
Landscaping Cloth	Great Horned Owl	92.5
Landscaping Cloth	Great Horned Owl	92.31
Landscaping Cloth	Great Horned Owl	84.71
Landscaping Cloth	Great Horned Owl	80.49
Landscaping Cloth	Harris's Sparrow	88.6
Leaf	Blue-winged Teal	98.03
Leaf	Brown-headed Cowbird	90.53
Leaf	Cedar Waxwing	92.02
Leaf	Common Yellowthroat	98.11
Leaf	Dark-eyed Junco	82.61
Leaf	Eastern Red Bat	87.65
Leaf	European Starling	84.91

Leaf	Fox Sparrow	97.26
Leaf	Fox Sparrow	97.04
Leaf	Fox Sparrow	93.18
Leaf	Fox Sparrow	90.97
Leaf	Fox Sparrow	81.19
Leaf	Garbage	96.38
Leaf	Harris's Sparrow	96.83
Leaf	Hoary Bat	94.76
Leaf	Hoary Bat	89.7
Leaf	Hoary Bat	86.43
Leaf	Hoary Bat	83.59
Leaf	Hoary Bat	83.38
Leaf	House Sparrow	91.11
Leaf	Northern Flicker	87.06
Leaf	Pine Grosbeak	86.91
Leaf	Swainson's Thrush	89
Leaf	Yellow-bellied Sapsucker	85.66
Leaf	Yellow-bellied Sapsucker	83.76
Plastic Bag	Snowy Owl	98.17
Puddle	Mallard	91.39
Rock	American Redstart	92.33
Rock	American Redstart	90.15
Rock	Barn Swallow	97.69

Rock	Barn Swallow	92.94
Rock	Barn Swallow	88.35
Rock	Barn Swallow	85.16
Rock	Barn Swallow	83
Rock	Barn Swallow	81.17
Rock	Barn Swallow	80.23
Rock	Black-crowned Night Heron	93.75
Rock	Blue-winged Teal	98.12
Rock	Blue-winged Teal	92.89
Rock	Blue-winged Teal	89.5
Rock	Bufflehead	98.21
Rock	Bufflehead	80.11
Rock	Dark-eyed Junco	81.09
Rock	Eastern Red Bat	99.4
Rock	Eastern Red Bat	95
Rock	Garbage	98.47
Rock	Garbage	95.11
Rock	Garbage	93.78
Rock	Garbage	85.03
Rock	Garbage	82.73
Rock	Hoary Bat	97
Rock	Mourning Dove	90
Rock	Ring-necked Pheasant	87.08

Rock	Silver-haired Bat	90.46
Rock	Swainson's Thrush	98.66
Rock	Swainson's Thrush	87.07
Sandbags	Black-crowned Night Heron	95.24
Sandbags	Snowy Owl	99.99
Sandbags	Snowy Owl	99.98
Sandbags	Snowy Owl	99.98
Sandbags	Snowy Owl	99.77
Sandbags	Snowy Owl	99.74
Sandbags	Snowy Owl	99.3
Sandbags	Snowy Owl	99.27
Sandbags	Snowy Owl	99.14
Sandbags	Snowy Owl	98.66
Sandbags	Snowy Owl	98.55
Sandbags	Snowy Owl	98.47
Sandbags	Snowy Owl	98.24
Sandbags	Snowy Owl	88.91
Sandbags	Snowy Owl	86.82
Shadow	American Coot	95.54
Shadow	American Coot	92.47
Shadow	American Coot	92.03
Shadow	American Coot	91.91
Shadow	American Coot	90.46

Shadow	American Coot	85.22
Shadow	American Redstart	94.06
Shadow	Brown-headed Cowbird	96.94
Shadow	Brown-headed Cowbird	80.92
Shadow	European Starling	95.77
Shadow	European Starling	94.65
Shadow	European Starling	94.59
Shadow	European Starling	91.13
Shadow	European Starling	88.86
Shadow	European Starling	88.76
Shadow	European Starling	86.9
Shadow	European Starling	86.42
Shadow	European Starling	84.38
Shadow	Ferruginous Hawk	97.36
Shadow	Gadwall	86.15
Shadow	Garbage	99
Shadow	Garbage	97.19
Shadow	Garbage	94.78
Shadow	Garbage	91.93
Shadow	Garbage	91.81
Shadow	Garbage	88.4
Shadow	Garbage	88.35
Shadow	Garbage	85.3

Shadow	Garbage	81.57
Shadow	Garbage	80.12
Shadow	Great Horned Owl	92.82
Shadow	Great Horned Owl	91.81
Shadow	Harris's Sparrow	93.21
Shadow	Harris's Sparrow	89.92
Shadow	Hoary Bat	93.15
Shadow	Little Brown Bat	91.16
Shadow	Ovenbird	93.65
Shadow	Red-tailed Hawk	95.01
Shadow	Red-tailed Hawk	94.64
Shadow	Red-tailed Hawk	82.42
Shadow	Red-winged Blackbird	99.66
Shadow	Red-winged Blackbird	94.42
Shadow	Red-winged Blackbird	91.29
Shadow	Red-winged Blackbird	91.25
Shadow	Red-winged Blackbird	88.18
Shadow	Red-winged Blackbird	87.32
Shadow	Red-winged Blackbird	86.36
Shadow	Red-winged Blackbird	85.95
Shadow	Rock Pigeon	86.53
Shadow	Rock Pigeon	85.34
Shadow	Silver-haired Bat	98.64

Shadow	Silver-haired Bat	93.54
Shadow	Silver-haired Bat	91.95
Shadow	Silver-haired Bat	84.32
Shadow	Snowy Owl	99.63
Shadow	Wood Duck	88.18
Shadow	Wood Duck	81.32
Shadow	Yellow Warbler	84.15
Shadow	Yellow-headed Blackbird	96.65
Shadow	Yellow-headed Blackbird	96.06
Shadow	Yellow-headed Blackbird	95.7
Shadow	Yellow-headed Blackbird	95.55
Shadow	Yellow-headed Blackbird	92.17
Shadow	Yellow-headed Blackbird	89.14
Shadow	Yellow-headed Blackbird	86.51
Shadow	Yellow-headed Blackbird	85.17
Shadow	Yellow-headed Blackbird	85.16
Shadow	Yellow-headed Blackbird	84.52
Shadow	Yellow-headed Blackbird	84.23
Shadow	Yellow-headed Blackbird	83.19
Snow	Black-crowned Night Heron	91.02
Snow	Black-crowned Night Heron	90.19
Snow	European Starling	86.31
Snow	Ferruginous Hawk	98.08

Snow	Ferruginous Hawk	95.72
Snow	Ferruginous Hawk	91.61
Snow	Ferruginous Hawk	87.69
Snow	Ferruginous Hawk	85.74
Snow	Ferruginous Hawk	83.49
Snow	Ferruginous Hawk	83.46
Snow	Ferruginous Hawk	83.12
Snow	Ferruginous Hawk	82.75
Snow	Ferruginous Hawk	82.3
Snow	Franklins Gull	97.35
Snow	Franklins Gull	95
Snow	Franklins Gull	88.22
Snow	Gadwall	82.43
Snow	Garbage	98.34
Snow	Garbage	97.94
Snow	Garbage	95.08
Snow	Garbage	92.34
Snow	Garbage	90.2
Snow	Garbage	90.02
Snow	Garbage	87
Snow	Garbage	86.96
Snow	Garbage	84.81
Snow	Garbage	83.26

Snow	Garbage	81.36
Snow	Garbage	80.57
Snow	Garbage	80.24
Snow	Great Horned Owl	89.23
Snow	Great Horned Owl	82.39
Snow	Great Horned Owl	81.14
Snow	Other Songbird	91.27
Snow	Other Songbird	87.02
Snow	Other Songbird	84.76
Snow	Other Songbird	80.7
Snow	Pine Grosbeak	99.29
Snow	Pine Grosbeak	98.87
Snow	Pine Grosbeak	95.59
Snow	Pine Grosbeak	90.55
Snow	Pine Grosbeak	88.6
Snow	Red-tailed Hawk	86.1
Snow	Sharp-tailed Grouse	85.32
Snow	Sharp-tailed Grouse	82.4
Snow	Snowy Owl	99.28
Snow	Snowy Owl	98.11
Snow	Snowy Owl	97.6
Snow	Snowy Owl	96.92
Snow	Snowy Owl	94.6

Snow	Snowy Owl	92.78
Snow	Snowy Owl	92.49
Snow	Snowy Owl	92.48
Snow	Snowy Owl	91.54
Snow	Snowy Owl	91.03
Snow	Snowy Owl	87.99
Snow	Snowy Owl	86.25
Snow	Snowy Owl	85.91
Snow	Snowy Owl	85.78
Snow	Snowy Owl	85.16
Snow	Snowy Owl	84.65
Snow	Snowy Owl	83.6
Snow	Snowy Owl	83.35
Snow	Snowy Owl	83.18
Snow	Snowy Owl	81.54
Snow	Snowy Owl	80.05
Snow	Snowy Owl	80.05
Stick	Barn Swallow	99.57
Stick	Barn Swallow	93.85
Stick	Garbage	97.68
Stick	Swainson's Thrush	91.04
Tarp	Snowy Owl	96.07
Tarp	Snowy Owl	87.3

Tree	Cooper's Hawk	83.31
Tree	Ferruginous Hawk	83.65
Tree	Harris's Sparrow	99.44
Tree	Harris's Sparrow	91.94
Tree	Red-tailed Hawk	93.07
Tree	Wood Duck	83.58
Tree	Wood Duck	82.72
Vegetation	American Redstart	86.03
Vegetation	American Redstart	86.02
Vegetation	Barn Swallow	92.41
Vegetation	Common Yellowthroat	93.16
Vegetation	Eastern Red Bat	94.6
Vegetation	Eastern Red Bat	93.73
Vegetation	Eastern Red Bat	86.22
Vegetation	Eastern Red Bat	81.18
Vegetation	Eastern Red Bat	80.73
Vegetation	Eastern Red Bat	80.63
Vegetation	European Starling	98.05
Vegetation	European Starling	95.11
Vegetation	European Starling	92.81
Vegetation	European Starling	86.08
Vegetation	Fox Sparrow	97.28
Vegetation	Fox Sparrow	96.02

Vegetation	Fox Sparrow	80.8
Vegetation	Franklin's Gull	84.14
Vegetation	Garbage	94.16
Vegetation	Garbage	88.16
Vegetation	Great Horned Owl	86.42
Vegetation	Great Horned Owl	84.4
Vegetation	Hermit Thrush	94.63
Vegetation	Hermit Thrush	93.33
Vegetation	Hermit Thrush	89.99
Vegetation	Hoary Bat	96.15
Vegetation	Hoary Bat	95.16
Vegetation	Hoary Bat	89.43
Vegetation	Hoary Bat	87.38
Vegetation	Hoary Bat	82.2
Vegetation	Hoary Bat	81.47
Vegetation	House Sparrow	84.31
Vegetation	Little Brown Bat	93.83
Vegetation	Northern Flicker	84.8
Vegetation	Ovenbird	86.18
Vegetation	Peregrine Falcon	82.31
Vegetation	Ring-necked Pheasant	93.19
Vegetation	Ring-necked Pheasant	86.89
Vegetation	Tree Swallow	90.6

Vegetation	White-throated Sparrow	86.79
Vegetation	Wood Duck	87.24
Vegetation	Yellow Warbler	92.8
Vegetation	Yellow Warbler	87.56
Vegetation	Yellow-headed Blackbird	95.7
Vegetation	Yellow-headed Blackbird	94.4
Vegetation	Yellow-headed Blackboard	94.78
Vehicle	Snowy Owl	96.01
Vehicle	Snowy Owl	82.39
Wood	Ferruginous Hawk	90.47
Wood	Red-tailed Hawk	94.58
Wood	Red-tailed Hawk	91.72

APPENDIX B. Species and total image counts used for the training and validation stages of building a convolutional neural network for post-construction mortality monitoring.

Species	Training Images	Validation Images
	Brown Model	
American bittern (*Botaurus lentiginosus*)	20	6
American coot (*Fulica americana*)	17	3
American redstart (*Setophaga ruticilla*)	23	4
American woodcock (*Scolopax minor*)	13	3
Barn swallow (*Hirundo rustica*)	5	1
Big brown bat (*Eptesicus fuscus*)	17	1
Black-crowned night-heron (*Nycticorax nycticorax*)	34	5
Blue-winged teal (*Spatula discors*)	60	13
Brown-headed cowbird (*Molothrus ater*)	22	3
Bufflehead (*Bucephala albeola*)	29	8
Cedar waxwing (*Bombycilla cedrorum*)	13	2
Chestnut-collared longspur (*Calcarius ornatus*)	3	1
Common redpoll (*Acanthis flammea*)	5	1
Common yellowthroat (*Geothlypis trichas*)	7	1
Cooper's hawk (*Accipiter cooperii*)	28	8
Dark-eyed junco (*Junco hyemalis*)	40	10
Eastern red bat (*Lasiurus borealis*)	50	13
European starling (*Sturnus vulgaris*)	21	5
Ferruginous hawk (*Buteo regalis*)	25	7

Fox sparrow (*Passerella iliaca*)	25	2
Franklin's gull (*Leucophaeus pipixcan*)	42	12
Gadwall (*Mareca strepera*)	26	7
Garbage	667	161
Great horned owl (*Bubo virginianus*)	41	9
Harris's sparrow (*Zonotrichia querula*)	5	2
Hermit thrush (*Catharus guttatus*)	5	10
Herring gull (*Larus argentatus*)	33	5
Hoary bat (*Lasiurus cinereus*)	66	17
House sparrow (*Passer domesticus*)	1	0
Little brown bat (*Myotis lucifugus*)	4	1
Mallard (*Anas platyrhynchos*)	87	19
Mourning dove (*Zenaida macroura*)	37	10
Northern flicker (*Colaptes auratus*)	43	13
Northern shoveler (*S. clypeata*)	20	5
Other songbird	2	0
Ovenbird (*Seiurus aurocapilla*)	23	6
Peregrine falcon (*Falco peregrinus*)	20	5
Pine grosbeak (*Pinicola enucleator*)	4	1
Red-headed woodpecker (*Melanerpes erythrocephalus*)	18	6
Red-tailed hawk (*Buteo jamaicensis*)	20	6
Red-winged blackbird (*Agelaius phoeniceus*)	15	7

Ring-billed gull (*Larus delawarensis*)	20	5
Ring-necked pheasant (*Phasianus colchicus*)	42	14
Rock pigeon (*Columba livia*)	20	2
Savannah sparrow (*Passerculus sandwichensis*)	3	1
Sharp-tailed grouse (*Tympanuchus phasianellus*)	21	7
Silver-haired bat (*Lasionycteris noctivagans*)	37	12
Snowy owl (*Bubo scandiacus*)	35	10
Swainson's thrush (*Catharus ustulatus*)	11	3
Tree swallow (*Tachycineta bicolor*)	1	0
White-throated sparrow (*Zonotrichia albicollis*)	38	10
Wood duck (*Aix sponsa*)	7	2
Yellow-bellied sapsucker (*Sphyrapicus varius*)	9	1
Yellow-headed blackbird (Xanthocephalus xanthocephalus)	16	6
Yellow warbler (*Setophaga petechia*)	19	6
	Green Model	
American white pelican (*Pelecanus erythrorhynchos*)	13	3
Garbage	289	72
Rock pigeon	6	2