THE RISE OF UNMANNED AIRCRAFT IN WILDLIFE SCIENCE: A REVIEW OF POTENTIAL CONTRIBUTIONS AND THEIR APPLICATION TO WATERBIRD RESEARCH

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April 2014

A thesis submitted to McGill University in partial fulfilment of the requirements of the degree of Ph.D. in Wildlife Biology

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ABSTRACT

The field of wildlife research and management tends to benefit from technological innovations such as remote sensing techniques that help to overcome the many challenges of studying and monitoring wild, free-ranging animals and their habitats. A new variety of remote sensing devices, unmanned aircraft systems (UAS), has recently become available for public and commercial use, promising to offer further support to wildlife science. Although a growing variety of preliminary efforts to apply UAS in the discipline have been undertaken, the technology is yet to gain any significant traction in practice. The overall aim of this project is to help stimulate and guide the adoption of UAS in wildlife science by taking a distinctly rigorous, contextualized and integrated approach. This is accomplished by first presenting a detailed analysis of potential applications for UAS throughout the field of wildlife science based on the results of a systematic review of the current primary literature. Two case studies involving waterbirds are then presented which serve to evaluate, validate and demonstrate the use of a small UAS in genuine management-driven contexts. The first case study, involving the least bittern (*Ixobrychus exilis*), highlights the benefits of the UAS for collecting fine-scale habitat data in a wetland habitat that is challenging to navigate and assess at ground level. The second case study, involving the common tern (*Sterna hirundo*), demonstrates the advantages of using a UAS for studying and monitoring species that are highly sensitive to investigator disturbance. The examples provided by these case studies as well as the additional applications proposed in the review suggest far-reaching potential for UAS in wildlife science.

RÉSUMÉ

Le domaine de l'étude et la gestion de la faune tend à tirer profit des innovations technologiques telles que les techniques de télédétection qui aident à surmonter les nombreux défis reliés à l'étude et au suivi des animaux sauvages et de leurs habitats. Un nouveau type d'instruments de télédétection, les systèmes d'aéronef sans pilote (UAS), est récemment devenu disponible pour usage public et commercial, promettant d'assister davantage les sciences fauniques. Bien qu'une variété croissante de tentatives préliminaires d'application de UAS dans le domaine ont été entreprises, la technologie tarde à percer dans la pratique générale. Cette thèse a pour but d'aider à stimuler et guider l'adoption des UAS dans les sciences fauniques en employant une approche distinctement rigoureuse, contextualisée et intégrée. Cela est accompli dans un premier temps en présentant un compte rendu détaillé des applications potentielles des UAS à travers le domaine des sciences fauniques, se basant sur les résultats d'un examen systématique de la littérature primaire actuelle. Dans un second temps, deux études de cas sur des oiseaux aquatiques sont présentées, servant à évaluer, valider et démontrer l'usage d'un UAS compact dans des contextes de gestion réels. La première étude de cas, sur le petit blongios (*Ixobrychus exilis*), met en valeur les bénéfices du UAS pour la collecte de données d'habitat à fine résolution dans un milieu humide difficile à parcourir et inventorier au sol. La seconde étude, sur la sterne pierregarin (*Sterna hirundo*), met en valeur les avantages du UAS pour l'étude et le suivi d'espèces très sensibles au dérangement causé par les chercheurs. Les exemples fournis par ces études de cas ainsi que les applications additionnelles proposées dans le compte rendu suggèrent un potentiel d'envergure pour les UAS dans les sciences fauniques.

ACKNOWLEDGEMENTS

I would like to thank my thesis supervisor, David Bird, for his tremendous and steadfast support throughout this project, both practical and moral. I thank my main field study collaborators, Vincent Carignan and Shawn Craik, for helping to conceptualize, design, coordinate and execute the research, as well as for providing advice and feedback throughout the analysis and writing process. I am grateful to the following individuals who helped with data collection or provided other support in various components of the project: Gilles Maillet, for assistance in all operations of the unmanned aircraft as well as much assistance in ground-based data collection throughout the common tern study; Hélène Gilbert and Audrey Lachance, for carrying out the ground-based habitat survey and compiling its results in the least bittern study; Benoit Jobin and Luc Robillard, for helping to identify vegetation in unmanned aerial imagery as well as assistance in least bittern surveys; Sylvain Giguère and Josée Tardif, for further assistance in least bittern surveys; Darla Saunders and Lindsay Laltoo, for assistance in GIS-related data generation and collection for the common tern study; Matthew Mahoney and David Colville, for providing digital elevation data for the common tern study; Eric Tremblay, for providing significant logistical and administrative support in the common tern study; Greg Lewis and Chris Tataryn, for on-site and technical support throughout the project in ensuring that the unmanned aircraft system functioned properly; and Murray Humphries and Meyer Nahon, for providing valuable general advice as members of my thesis advisory committee. Further individuals are acknowledged for minor contributions unrelated to data collection in each chapter of this thesis.

Funding and in-kind contributions for this project were provided by the Kenneth M. Molson Foundation, the Canadian Wildlife Federation, the New Brunswick Wildlife Trust Fund, Environment Canada, Parks Canada, the Ministry of National Defence, Aerial Insight, MicroPilot, Pix4D, and the Fonds Québécois de la Recherche sur la Nature et les Technologies.

I would finally like to thank my parents for their tremendous moral support as well as my wife for much moral as well as general scholarly support.

PREFACE

The following is a manuscript-based thesis consisting of an introduction, five data chapters and a final summary and conclusion. The Ph.D. candidate is primary author of all chapters and the candidate's thesis supervisor, David M. Bird, is co-author of all chapters. Chapter 2 is formatted for the *Journal of Unmanned Vehicle Systems*, in which it has been published. Chapter 3 is additionally co-authored by Vincent Carignan, who assisted with study coordination and data collection and provided advice throughout the analysis and writing process. It is formatted for *Wetlands*, in which it has been published. Chapters 4 and 5 are additionally co-authored by Shawn R. Craik, who provided general study guidance, assisted with experimental design and data collection, and provided advice throughout the analysis and writing process. Chapter 4 is formatted for upcoming submission to *Waterbirds* and Chapter 5 is formatted for upcoming submission to the *Journal of Field Ornithology*.

Chapter 1 represents the first comprehensive review of potential applications for unmanned aircraft throughout wildlife science, and the first review of their potential applications in any field to use a quantitative, systematic literature review approach. Chapter 2 represents the first empirical evaluation of a small fixed-wing unmanned aircraft for collecting land cover data over a wetland. Chapters 3 and 4 are the first examples of fully integrated applications of an unmanned aircraft in standard, biology-oriented wildlife studies, in which the aircraft is a mere component of the methods rather than the main focus of the research. Chapter 4 is additionally the first study of common tern habitat preferences to use an information-theoretic approach to data analysis, providing new insight into the relative importance of different habitat variables. Finally, Chapter 5 represents the most rigorous comparative evaluation to date of an unmanned aircraft for surveying wild animals and the first to use hypothesis-testing statistical analyses.

INTRODUCTION AND OBJECTIVES

Wildlife science is a melting pot of pure and applied research on non-domesticated species. The broadest definition of wildlife may include flora, although the term conventionally refers exclusively to fauna, and most commonly in the scientific community to birds, mammals, reptiles and amphibians (the latter two jointly referred to as herptiles); in other words, all air-breathing vertebrates with the exception of lungfish. The terms wildlife *research* (or *biology*) and *management* tend to evoke the pure and applied aspects of the discipline, respectively, but in practice they often overlap and can be difficult to differentiate. Management can refer to conservation of threatened species, but more broadly it refers to the practice of balancing the needs of wildlife with those of humans, including management of game species and persecution or eradication of species considered to be pests. In all cases, effective wildlife management requires a robust foundation of scientific knowledge drawn from such fields as ecology, natural history, evolution, genetics and physiology. Finally, wildlife science is a distinctly contemporary discipline, routinely faced with pressing issues (e.g. halting the decline of threatened species or the damage caused by nuisance species) and constrained by limited resources.

Moreover, wildlife by its very nature tends be challenging to study and manage. This is because species of interest often tend to avoid humans or developed areas, be cryptic or otherwise elusive, range over very large areas, be acutely sensitive to disturbance, or be aggressive and dangerous to approach. Moreover, the habitats they occupy tend to be remote, expansive or difficult to navigate. Consequently, wildlife science has historically derived great benefits from various technologies that help to overcome these challenges. Aircraft, for example, allow practitioners to access remote locations, rapidly cover large areas, and conveniently navigate over rugged habitats (Fleming and Tracy 2008). Satellite-borne sensors can remotely collect wildlife habitat data over vast or inaccessible expanses (Kerr and Ostrovsky 2003). Radars can be used to detect and enumerate birds or bats flying at night or at distances and heights beyond the range of visual observers (Larkin 2005). Infrared thermal cameras can detect the heat signatures of endothermic animals at night or through the canopy where they would otherwise be concealed (O’Neil et al. 2005). Stationary camera traps help to catch glimpses of highly elusive animals (O'Connell et al. 2011). A wide array of animal-borne electronic tracking devices allow animals to be remotely monitored or relocated via satellite telemetry, short-range radio telemetry or subsequent recapture and retrieval of logged data (Thomas et al. 2011). Finally, technology has enhanced our ability to capture animals using such means as sophisticated stationary traps, cannon/rocket nets and net guns, and chemical immobilization agents delivered via projectile (Roffe et al. 2005, Schemnitz 2005).

The twenty-first century has seen a steady rise in the development and application of a new breed of remote sensing devices that promise to offer further support to wildlife science: unmanned aircraft systems (UAS), also called unmanned aerial vehicles (UAV) and popularly known as drones. Unmanned aircraft have been used for decades by militaries (Newcome 2004), but it is only recently that the technology has become sufficiently affordable, accessible and user-friendly to be suited to civilian applications. Many modern UAS superficially resemble conventional radio-controlled model aircraft (both fixed-wing and rotary-wing), which have been flown by hobbyists for many decades, but the former differ in that they typically feature some form of on-board automated system that lessens or removes the burden of real-time control by human operators (Austin 2010). Many are capable of fully autonomous execution of preprogrammed flights, while others facilitate live remote piloting by means of automatic stabilization assistance, fine-scale control of the aircraft based on general commands transmitted by ground operators, or transmission of detailed flight information (e.g. speed, altitude, position, on-board video) to operators to assist manual piloting. Computerization of UAS also enables sophisticated use of payloads such as cameras, lasers, meteorological instruments, or dispenser mechanisms.

It is popularly proclaimed that UAS are ideal for "dull, dirty and dangerous" missions, and they are generally recognized for their ability to unobtrusively gather aerial data at finer resolutions or in a more timely and repeatable fashion than conventional aircraft or satellite-borne sensors. As such, applications for UAS have arisen in agriculture (Zhang and Kovacs 2012), wildfire monitoring (Merino et al. 2012), search and rescue (Goodrich et al. 2009), meteorology (Martin et al. 2011), ice and surface oceanography (Inoue et al. 2008), volcano research (McGonigle et al. 2008), aerobiology (Techy et al. 2010), archeology (Hendrickx et al.

2011), pipeline and transmission line inspection (Yang et al. 2012, Frish et al. 2013), and management and monitoring of rangelands (Laliberte et al. 2011), wetlands (Knoth et al. 2013) and forests (Wing et al. 2013). Rudimentary fixed-wing and lighter-than-air models previously made limited contributions to wildlife science and general ecology (e.g. Jonsson et al. 1980, Flamm et al. 2000, Murden and Risenhoover 2000, Thome and Thome 2000, Nowacek and Tyack 2001, Abd-Elrahman et al. 2005), but the advent of modern fully- and semi-autonomous UAS has triggered a new wave of interest in what this technology might offer to the discipline.

Jones et al. (2006) set efforts in motion when they reported on detection of various wildlife species—namely wading birds, alligators and manatees—by a 1.5-m wingspan, fully autonomous UAS. Since then, further endeavours have been directed at using UAS to survey marine mammals (additionally including cetaceans and pinnipeds), partly as a way to avoid the hazards of manned aerial surveys in remote offshore locations (Koski et al. 2009, NOAA 2009, Koski et al. 2010, Martin et al. 2012, Koski et al. 2013). Efforts have also been invested in UAS bird surveys, particularly waterbirds (Watts et al. 2010, Chabot and Bird 2012, Sarda-Palomera et al. 2012). Small UAS have been explored as an economical means of monitoring priority species for conservation, such as elephants, in developing nations (Koh and Wich 2012, Vermeulen et al. 2013). There are ongoing efforts in the field of robotics to develop UAS capable of automatically seeking out radio-marked animals (Posh and Sukkarieh 2009, Soriano et al. 2009, Korner et al. 2010). Finally, small UAS have been touted as convenient tools for gathering timely, high-resolution wildlife habitat imagery (Rodriguez et al. 2012).

Collectively, these efforts suggest considerable potential for modern UAS in wildlife science. However, in practice they have gained little traction to date, as evidenced by the fact that not a single one of the above-cited publications is a standard biology-oriented research article; they are all either anecdotal or qualitative reviews, or methods-oriented articles (i.e. proof-of-concept) focused on contemplating or demonstrating the use of UAS in various applications, mostly preliminary in nature and often lacking broader context. Although UAS will likely be increasingly adopted in ecology and wildlife science (Anderson and Gaston 2013), even if very gradually, I argue that practitioners will tend to remain reluctant to consider them absent more compelling evidence of their usefulness than has been published to date; in other words, they will tend to dismiss them as complicated, unfamiliar and unproven. Since time and resources are typically of the essence in wildlife research and management, it is in the best interest of the field for innovative and beneficial new methods to be adopted expeditiously. I believe that compelling evidence of the usefulness of UAS can be provided by: (1) more detailed, focused and systematic reviews of their potential applications in wildlife science; (2) more rigorous and contextualized method evaluation/validation studies; and (3) demonstrations of their contribution to genuine wildlife research- and management-driven studies, as mere components of the methods rather than the focus of the work.

Thus, the overall aim of this thesis is to deliver all three of these elements. I first present a systematic literature review (Chapter 1) that aims to offer more detailed insight than previous reviews on areas within the broad sphere of wildlife science that are likely to benefit from the application of UAS. Next, I present two management-driven case studies focused on waterbird species, each involving both validation and novel application of a small "off-the-shelf" autonomous fixed-wing UAS. The first (Chapters 2–3) was motivated by the need to manage a wetland impoundment in Baie-du-Febvre, Quebec, in order to promote continued occupation by an important breeding population of threatened least bitterns (*Ixobrychus exilis*) for which local habitat preferences were poorly described. The second (Chapters 4–5) was motivated by the need to investigate habitat relahionships of common terns (*Sterna hirundo*) in the third largest breeding colony of the species in North America. The colony is situated on a coastal barrier island complex in Kouchibouguac National Park, New Brunswick, that is threatened by erosion and rising sea level and may eventually require habitat conservation efforts. In addition, there was interest in developing a low-disturbance alternative to laborious and highly disruptive ground-based population surveys of the colony. For both case studies, I was the chief operator of the UAS, drawing on experience acquired over the course of a previous thesis research project (Chabot 2009).

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CONNECTING STATEMENT

The first objective of this project is to provide a detailed review of potential applications for UAS in the broad field of wildlife science. The following chapter addresses this objective and presents a systematic review of current primary wildlife science literature to support conclusions. This chapter also serves as a more in-depth review of UAS literature than presented in the preceding introductory chapter with regard to publications that are relevant to wildlife science.

CHAPTER 1

WILDLIFE RESEARCH METHODS IN THE 21ST CENTURY: WHERE WILL DRONES FIT IN?

Abstract

There has been growing anticipation for small unmanned aircraft systems (UAS) to break through as data collection instruments in the field of wildlife research and management, but in practice they have gained limited traction to date. To better inform practitioners of the potential opportunities offered by small UAS, we present a systematic review of current primary wildlife literature with the aim of identifying areas of research that are likely to benefit from this burgeoning technology, based on three major anticipated applications: visual observation and surveying of animals, habitat sensing, and automated telemetry tracking. As a general prediction, we submit that small UAS will tend to be useful for similar tasks as performed by conventional aircraft, but at an intermediate spatial scale between the latter and ground-based investigations. Trends in the literature suggest that there is strong potential for small UAS to perform precise and unobtrusive surveys of animals that congregate in predictable locations, such as colonial waterbirds and pinnipeds. Highly manoeuvrable rotary-wing models should be considered for up-close observation of hard-to-reach tree-, cliff- and manmade structure-dwelling or -breeding animals. UAS-based habitat sensing will be especially beneficial in a variety of situations where timely, fine-scale data are required in areas that are laborious or impractical to survey at ground level, such as dense wetlands. Finally, small UAS soon promise to facilitate telemetry tracking of species occupying small to medium home ranges in rugged or GPS-impeded habitats, including a variety of birds, small rodent-like mammals, small carnivorans (e.g. mustelids), bats, primates, snakes, lizards and land-dwelling turtles.

Introduction

For several decades, aircraft have been heavily relied upon in the field of wildlife research and management. They provide the ability to rapidly and conveniently cover large, remote and/or rugged areas in which species of interest occur, as well as perform remote sensing of wildlife habitats (Wulder et al. 2004, Fleming and Tracey 2008). Since around the turn of the century, a new breed of aircraft has been emerging: unmanned aircraft systems (UAS), popularly referred to as drones. Although radio-controlled model aircraft have existed for several decades, modern UAS differ in that they typically feature some form of on-board automated system that lessens or removes the burden of controlling the aircraft from human operators and delivers much more precise navigational performance. Computerization also allows sophisticated control over on-board sensors such as cameras. As their applications steadily multiply, UAS are now commonly professed to constitute safer, cheaper, more convenient, more discreet and/or more precise alternatives to conventional aircraft.

Although UAS come in a wide variety of sizes and configurations, essentially two types are poised to become widely available for public/commercial use: small low-altitude, short-endurance (LASE) fixed-wing models (<5 kg, <3 m wingspan, <300 m altitude, <2 hr endurance) and small vertical take-off and landing (VTOL) rotary-wing models (Watts et al. 2012). The latter are typically smaller than the former, fly at lower altitude (<100 m) and have shorter endurance (<30 min), but offer the unique hovering capability of helicopters in a size factor that allows highly precise small-scale manoeuvring. Both types usually feature relatively quiet electric motors powered by rechargeable batteries. As potential scientific research instruments, these UAS might generally be surmised to specialize in collecting data at an intermediate spatial scale between conventional aircraft and direct on-the-ground measurements and observations. Assessments and implementations of UAS have slowly multiplied in the field of wildlife research and management. Based on the existing literature, we foresee at least three major types of applications for UAS in wildlife science in the near future.

The first, visual observation and surveying of animals, has received the most coverage to date in the scientific literature. Abd-Elrahman et al. (2005) and Jones et al. (2006) first reported on the detection of various wading bird species in wetland and agricultural habitats using small fixed-wing UAS, with a further anecdotal account provided by Watts et al. (2010). Chabot and Bird (2012) compared staging migratory flock counts of Canada geese (*Branta canadensis*) and Snow geese (*Chen caerulescens*) obtained from UAS aerial photos to ground counts, and Sarda-Palomera et al. (2012) used a small UAS to census an island-breeding colony of Black-headed gulls (*Chroicocephalus ridibundus*). Marine mammals have also been the subject of several UAS-related publications, with short-range manatee surveys using small fixed-wing UAS reported by Jones et al. (2006) and Martin et al. (2012), while Koski et al. (2009, 2010, 2013) have explored the feasibility of conducting long-range offshore marine mammal surveys (including large cetaceans and pinnipeds) using larger high-endurance UAS, primarily as a means to substitute hazardous flights by manned aircraft in these remote expanses. Other terrestrial wildlife detected by small UAS include elephants (*Elephas maximus* and *Loxodonta africana*), Orangutans (*Pongo abelii*), American alligators (*Alligator mississippiensis*) and farmed Bison (*Bison bison*) (Jones et al. 2006, Watts et al. 2010, Koh and Wich 2012, Vermeulen et al. 2013).

The second type of application, habitat sensing, has received considerable coverage in the remote sensing and general environmental/ecosystem science literature but only limited coverage in direct relation to specific wildlife species. In particular, small fixed-wing UAS have been in use for about a decade for high-resolution (<10 cm/pixel) vegetation and land cover sensing over rangelands (Hardin and Jackson 2005, Rango et al. 2006, 2009, Breckenridge and Dakins 2011, Laliberte et al. 2011a), and they have also been used for forest habitat sensing (Dunford et al. 2009, Hervouet et al. 2011, Getzin et al. 2012, Wing et al. 2013). For even finer-scale sensing, small rotary-wing UAS have been used to gather very low-altitude data (Goktogan et al. 2010, Breckenridge et al. 2012, McGwire et al. 2013, Knoth et al. 2013). In direct relation to wildlife species, Rodriguez et al. (2012) used data loggers to track foraging flight paths of Lesser kestrels (*Falco naumanni*) and subsequently programmed the paths into a UAS in order to gather high-resolution “quasi-real-time” imagery of the birds’ foraging habitats. Chabot and Bird (2013) used a small UAS to finely map the water-vegetation interface of a wetland impoundment for a habitat study of the Least bittern (*Ixobrychus exilis*), highlighting advantages over conventional ground-based surveys in terms of data precision and ease and efficiency of data collection.

The third type of application, wildlife telemetry tracking, has thus far only received attention in the scientific literature as a theoretical curiosity in the field of robotics (Posh and Sukkarieh 2009, Soriano et al. 2009, Korner et al. 2010), but we believe it could have significant potential throughout the field of wildlife research and management once it can be put into practice, likely within the next few years. The basic concept is that a small autonomous UAS equipped with an antenna-receiver system is programmed to fly a systematic search pattern at low altitude (<150 m) over a given area until it detects a signal from a radio-tagged animal. An on-board computer then begins triangulating the origin of the signal and feeding new waypoints to the autopilot so as to direct the aircraft towards the subject. Once the subject is reached (point of maximum signal strength), the UAS may simply record its location, or perform further tasks such as gather imagery of the subject and/or the surrounding area or download data from an activity logger on the animal via radio link.

Notwithstanding the aforementioned literature, in practice UAS have gained limited traction to date in wildlife science: there has yet to be a single primary publication in which a UAS is a mere component of the methods in a biology-oriented study rather than the main focus of the paper. Many wildlife practitioners remain unfamiliar with UAS and their capabilities, while others may be reluctant to consider them due to their novelty and lack of precedent for numerous potential applications. Useful reviews of current UAS technology and considerations of use in ecology and broader scientific research are provided by Watts et al. (2012) and Anderson and Gaston (2013), however their overviews of potential applications are rather general, as those outlined above, and may therefore be overlooked by practitioners in specialized disciplines who could in fact benefit from them.

With this review, we aim to provide more detailed, empirically supported insight to practitioners into areas—in particular specific types of species—within the broad sphere of wildlife science that seem likely to benefit from use of UAS in relation to the three major applications proposed above. Based on the premise that UAS will tend to be useful for similar tasks as performed by conventional aircraft, but at generally smaller spatial scales, we undertake a systematic review of primary wildlife literature to identify and quantify current uses of manned aircraft, satellites (which are commonly used for habitat sensing) and electronic animal tracking devices throughout the discipline. We then discuss whether UAS could be beneficial substitutes in areas where conventional aerial methods are currently employed, as well as whether they could break new ground in areas where aerial methods are *not* currently employed.

Methods

We systematically searched for primary wildlife-related literature published since the year 2000 alluding to use of aircraft, satellites, or electronic animal tracking devices. We compiled a list of 67 search terms (Table 1) in an effort to maximize relevant results, while avoiding overly nonspecific terms so as not to be swamped with irrelevant results. We performed searches in the Web of Science (WoS; Thomson Reuters Corp., New York, NY, USA) using Boolean notation (i.e. "OR" separators between terms, quotations around multi-word terms, "*" to search for all variants of certain words) to incorporate all search terms into a single sequence. We searched all relevant wildlife-specific publications with indexed records since 2000 (Table 2)—including all publications with titles containing the word "wildlife" (eight in total, excluding the Journal of Wildlife Diseases, the Journal of Wildlife Rehabilitation, and the Journal of Zoo and Wildlife Medicine), all bird-specific publications (22 in total), all mammal-specific publications (16 in total) and all herptile-specific publications (15 in total)—totalling 43,118 records as of 10 November 2013.

The search returned a total of 4,704 results. In an initial filtering stage, we quickly scanned through the titles, abstracts and keywords of results in the WoS (with search terms automatically highlighted) and discarded all records containing obviously irrelevant occurrences of search terms (e.g. "aerial display/hawking/insectivore/predator", "airborne pollutant", "satellite population/DNA", "radio-immunoassay/graph", ground-based infrared/thermal sensing, studies on effects of commercial or military aircraft on wildlife), 903 in total. Remaining results (3,801) were then exported to EndNote X7 (Thomson Reuters Corp., New York, NY, USA) for more detailed cataloguing and analysis. We first performed coarse sorting of records by searching select combinations of the original search terms within the EndNote library in order to isolate records alluding to use of aircraft, satellite, or tracking devices. When unclear based solely on the title, abstract and keywords, we accessed the full text of records to determine whether they involved aircraft or satellite, for example when the only search term present in the record summary was “remote sensing”, “land cover” or “digital elevation model”.

We then scanned each record in order to extract a series of qualitative variables describing the focus and methods involved in the article. For all records, we categorized subject species as birds, mammals or herptiles (hereafter herps). Whenever possible, we further categorized birds into raptors (orders Accipitriformes, Falconiformes and Strigiformes), waterbirds (waterfowl-like, seabird-like, shorebird-like, and wading bird-like), landfowl-like birds (orders Galliformes and Pteroclidiformes, some rails and bustards), and all other “small birds” (orders Passeriformes, Apodiformes, Piciformes, Coraciiformes, Caprimulgiformes, Columbiformes, Psittaciformes, Cuculiformes, Trogoniformes and Coliiformes). The latter group is disproportionately diverse and contains some arguably “large” species (e.g. ravens, large parrots), however its members generally do not lend themselves to aerial surveys. We further categorized mammals into marine mammals (cetaceans, pinnipeds and sirenians), large herbivores (terrestrial ungulates and large marsupials), carnivores (order Carnivora and some larger carnivorous marsupials such as quolls, *Dasyurus* spp., and Tasmanian devils, *Sarcophilus harrisii*), primates, bats, and all other terrestrial “small mammals” (notably rodents, lagomorphs, insectivorans, and small and arboreal marsupials). Finally, we further categorized herps into sea turtles, land turtles (and tortoises), crocodilians, lizards, snakes, frogs (and toads), and salamanders (and newts). We also noted the main thrust of each record using the tags “biology”, “methods”, “management” and “review”, applying more than one tag per article where appropriate.

For records alluding to aircraft, we categorized applications into visual observation (direct observation of animals or indirect signs such as tracks, also noting any mentions of specific sensors such as photo, video or infrared), telemetry (aerial radio-tracking of animals), shooting (shooting animals from helicopters to either cull them, capture them using dart or net guns, or mark them using paintball guns), baiting (aerial distribution of baits containing poison, vaccines or contraceptives), and habitat sensing (including land cover/use, topography and vertical vegetation structure). For articles alluding to habitat assessment via satellite-borne sensors, we also noted the type of data obtained (e.g. land cover, ice cover, topography, surface temperatures, vegetation greenness indices). For articles alluding to electronic tracking devices, we distinguished between typically larger satellite- and GPS-based telemetry devices (e.g. GPS collars, Argos platform transmitter terminals aka PTTs) and smaller short-range radio telemetry devices as well as simple data loggers that require physical retrieval. It should be noted that data retrieval from some GPS-based devices is accomplished via short-range radio telemetry or mobile phone networks (GSM) and that these devices are smaller than those that allow tracking via satellite uplink.

Finally, we focused data analysis on contrasting absolute and relative frequencies of values for variables of interest among journals, and among and within categories of animals.

Results

We found 613 total records alluding to aircraft use. Their relative frequency (percentage of relevant records among total records) was substantially higher across "wildlife" journals (4.85%) than bird (1.04%), mammal (0.72%) and herptile journals (0.17%). Among journals with ≥200 total records in the WoS and ≥1% frequency of aircraft-related records (14 in total), six were "wildlife" journals (including five of the top seven), five were bird journals, led by *Waterbirds*, and three were mammal journals, led by *Marine Mammal Science* (Fig. 1). Aircraft-related records from "wildlife" journals were also 2.4 times more frequently tagged as "methods" articles (51.71%) than those from class-specific journals (21.80%).

Among the 613 aircraft-related records, 410 involved visual observation (Fig. 2), most frequently of waterbirds (130), large mammalian terrestrial herbivores (117) and marine mammals (84), with considerably fewer records involving observation of raptors (21), mammalian carnivores (21), small mammals (9), landfowl (8), crocodilians (6) and sea turtles (4). We found a single record of aerial observation of a small bird: a large cliff-nesting colony of Burrowing parrots (*Cyanoliseus patagonus*). We found no records of primates, bats or smaller herps than sea turtles and crocodilians being visually observed from aircraft. Indirect observation accounted for 10/21 records of mammalian carnivore observation (in all cases tracks) and all but one record of small mammal observation (including seven records of aerial surveys of Prairie dog *Cynomys* spp. colony burrows), with the relatively large Capybara (*Hydrochoerus hydrochaeris*) being the only small mammal directly observed by aerial survey. Waterfowl (65 records) were the most frequently observed waterbirds (Fig. 3), followed by sea birds (27), wading birds (24) and shorebirds (9); while cetaceans (35) were the most frequently observed marine mammals (Fig. 4), followed by pinnipeds (30) and sirenians (15). Aerial infrared thermal imaging was used to observe animals in 13 records, of which eight involved various terrestrial ungulates, three involved walruses (*Odobenus rosmarus*) and two involved large birds.

Another 31 records alluded to shooting animals from aircraft in order to cull, capture, or mark, all of them terrestrial ungulates or mammalian carnivores except for a single record of owl capture by net gun from a helicopter. A further 30 records alluded to aerial baiting, 27 of which involved poisoning of various pest species. We also found four records that involved teaching migration routes to large captive-bred waterbirds by training them to follow an ultralight aircraft.

We found 112 records alluding to aerial habitat sensing, compared to 249 records of satellite-based habitat sensing. Collection of land cover data was involved in 87.5% of aircraft-related records, compared to 75.9% of satellite-related records. Only a single aircraft-related record involved collection of topographical data, compared to 13.3% of satellite-related records, however five aircraft-related records involved collection of fine-scale vertical vegetation structure data using lidar (four relating to small birds and one to squirrels). Collection of normalized difference vegetation index (NDVI) data occurred in 15.7% of satellite-related records. Looking at the relative proportion of aircraft- vs. satellite-based habitat sensing records within different groups of animals (Fig. 5), small birds had the highest proportion of aircraft-derived data (41.4%), followed by raptors (40.5%), landfowl (37.5%), small mammals (35.3%), amphibians (31.3%) and waterbirds (28.9%). Habitat sensing for large mammalian herbivores (14.3%), primates (20.0%) and carnivores (22.9%) was relatively more dominated by satellite-derived data.

We found 3,119 records alluding to use of electronic animal tracking devices, but only 51 of these (summarized by category of animal in Fig. 6) contained explicit mention of tracking by aircraft in the title, abstract or keywords. Marine mammals tracked by aerial telemetry were limited to pinnipeds and sirenians; waterbirds included waterfowl, small shorebirds and small to large seabirds; raptors ranged in size from small Burrowing owls (*Athene cunicularia*) to Turkey vultures (*Cathartes aura*); and mammalian carnivores ranged from Coyotes (*Canis latrans*) to bears. A single record of aerial telemetry tracking of a small mammal was found: the Brush-tailed bettong (*Bettongia penicillata*). Among the 3,119 total records, 672 involved satellite- or GPS-based telemetry devices and 2,447 involved radio-based telemetry devices or simple data loggers. Frequencies of the former and latter devices by category of animal are shown in Fig. 7, revealing a predictable general pattern of decreasing relative frequency of satellite-GPS devices in relation to radio-logger devices with decreasing animal size, although examples were found of the former devices being used on animals as small as European hedgehogs (*Erinaceus europaeus*), Straw-colored fruit bats (*Eidolon helvum*), Blue-tongued skinks (*Tiliqua* spp.) and small shorebirds. The pattern was also observed within categories of animals with widely ranging sizes. For example, within mammalian carnivores we found radio-logger-related records involving numerous species of mustelids (including relatively small *Mustela* spp.), whereas satellite-GPS devices were only used on larger Wolverines (*Gulo gulo*) and otters (*Lutra* spp.); whereas most raptor species are large enough to carry satellite-GPS devices, radio-logger-related records were dominated by small owls; and whereas large seabirds can carry satellite-GPS devices, radio-logger-related records were dominated by relatively small auklets, murrelets and terns. For large animals on which both categories of devices were used (e.g. raptors, large seabirds, some mammalian herbivores), satellite-GPS devices were more typically used to track annual long-distance migrations whereas radio-logger devices were used to study smaller-scale seasonal home ranges.

Discussion

Throughout the systematic review process, it became evident that use of aircraft for animal observation, telemetry and habitat sensing (as well as satellite-based habitat sensing) frequently goes unreported in article titles, abstracts and keywords. On several occasions when we needed to access the full text of records, further applications of aircraft were revealed that were not mentioned in the record summary. Other times, additional uses of aircraft were strongly implied through the general descriptions in abstracts, though not explicitly confirmed by the presence of our specific search terms. Since we relied on our fixed set of search terms to perform an unbiased probe of the selected body of literature, we did not count these additional “unexpected” cases in our dataset as countless more such cases would have been entirely missed in the initial WoS search whenever record summaries did not contain any of our search terms. The reason aircraft and satellite use often goes unreported is likely because these methods are so well established that they are deemed unnecessary to explicitly mention in abstracts, especially in biology-oriented articles. In all likelihood, the much higher relative frequency of aircraft-related records found in “wildlife” journals is a direct consequence of their greater tendency, as we observed, to publish methods- or management-oriented articles that more commonly contained our search terms in their abstracts. Despite having likely failed to capture a large number of articles involving aircraft or satellite use, we believe that we collected a sufficient sample to be able to draw sound conclusions.

Visual observation

The most frequently observed animals by aerial survey were waterbirds, large mammalian terrestrial herbivores, and marine mammals (Fig. 2). Waterbirds tend to be large enough to view from aircraft and tend to conspicuously aggregate in open areas during such activities as breeding, migrating, foraging and moulting. They also tend to occur in fully or semi-aquatic habitats that can be difficult to access at ground level. Conventional aircraft can navigate from aggregation to aggregation (with on-board observers often tasked with spotting them from a distance) over large areas in the span of a single flight, making them an efficient means of surveying waterbirds (Kingsford and Porter 2009). To date, primary literature accounts of bird observation using UAS have exclusively involved waterbirds (Abd-Elrahman et al. 2005, Jones et al. 2006, Watts et al. 2010, Chabot and Bird 2012, Sarda-Palomera et al. 2012). Conventional aircraft are likely to remain the best option for large-scale waterbird surveys as described above due to the endurance and range limitations of small UAS. Only in very remote areas or over expansive bodies of water where manned flight is hazardous would it make sense to consider using longer-endurance UAS. However, we foresee significant potential for small UAS in small-scale waterbird surveys (i.e. individual aggregations), particularly for smaller species that are more challenging to detect from conventional aircraft (e.g. terns, small alcids, shorebirds) and consequently tend be surveyed from the ground. Ground surveys can be very accurate but also physically laborious and disturbing to birds, particularly in breeding colonies (Carney and Sydeman 1999). Low-altitude, high-resolution UAS surveys promise to approach the precision of ground surveys, and initial accounts suggest they may cause little to no disturbance (Chabot and Bird 2012, Sarda-Palomera et al. 2012).

Large mammalian terrestrial herbivores tend to range over expansive areas that may additionally be rugged and/or remote, making aircraft an obvious solution for surveying them. Even when they are concealed under the canopy, their large bodies emit thermal signatures that can be readily detected by airborne infrared cameras (e.g. Dunn et al. 2002, Kissell and Nimmo 2011). Because of these animals' large ranges, we see limited opportunity for small short-range UAS to be of use for visual surveys. Vermeulen et al. (2013) assessed a small UAS as a potentially inexpensive means of censusing elephant populations in Burkina Faso but concluded that limited flight endurance precluded its application at a sufficient scale to be useful. Operation at such scales will require more expensive and sophisticated long-endurance UAS, which will likely be most advantageous in very remote areas where manned flight is hazardous. Efforts undertaken by Koski et al. (2009, 2010, 2013) to conduct long-range offshore marine mammal surveys with UAS are entirely motivated by human safety considerations. Otherwise, short-range UAS will only have potential utility for surveying marine mammals that congregate in predictable locations. This is the case for many breeding pinnipeds, which accounted for 37.5% of literature records related to marine mammal aerial visual surveys. Sirenians (18.8% of marine mammal surveys) also tend to congregate during winter in warm, shallow waters, for example in spring-fed rivers and near power plant discharge canals where they can be readily surveyed from aircraft (e.g. Laist and Reynolds 2005, Edwards et al. 2007), including UAS (Jones et al. 2006, Martin et al. 2012).

Animals that are less frequently visually observed from aircraft (Fig. 2) may tend not to lend themselves to aerial detection or may simply receive less total research effort with regard to population monitoring. The former explanation would certainly seem to apply to mammalian carnivores, small mammals and small birds. Many carnivores are large enough to be viewed from aircraft, but they tend to be sparsely distributed and elusive, as evidenced by half of their aerial survey records involving detection of their tracks rather than the animals themselves (Fig. 2). We envisage little opportunity for UAS to visually survey these species. Small mammals and small birds tend to be too small or concealed (e.g. canopy, ground-level vegetation, cavities and burrows) to survey from aircraft and likely from fixed-wing UAS. However, we suggest that small rotary-wing UAS could offer unique opportunities to observe some of these species at the individual rather than population level. They can be deployed in relatively confined spaces (e.g. from under the canopy) and could, for example, conveniently peek at tree-, cliff- or manmade structure-dwelling species that would otherwise be challenging or hazardous to reach. This technique might also be applied to raptor nests, which are often difficult to access or vigorously defended, tree- or cliff-dwelling bats, as well as arboreal primates that are generally constrained to being observed from the ground. Finally, we see limited opportunity for UAS to visually observe herps, which are either best surveyed from the ground in the case of small species or over large areas using conventional aircraft in the case of large species (sea turtles and crocodilians), although Jones et al. (2006) and Watts et al. (2010) reported incidental alligator detections during UAS flights in Florida.

Habitat sensing

For many wildlife habitat studies, low-resolution (1 m to several km per pixel) satellite-derived data, which can be conveniently and often freely obtained, are sufficient to meet research needs. In other cases, finer-scale or more timely data are required, leading to the use of aircraft-derived data or ground-based habitat measurements. While ground-based data collection is typically much more precise and accurate, it can also become very time-consuming as the area of interest grows larger or in hard-to-navigate habitats such as wetlands. This is a good example of where there exists a significant “gap” between the spatial scale of data collected on the ground and those collected by conventional aircraft that small UAS may be able to fill, and there are already examples of them doing so in rangeland and forest habitats (Breckenridge and Dakins 2011, Hervouet et al. 2011, Laliberte et al. 2011a, Getzin et al. 2012). It is difficult to predict precisely where such gaps may exist throughout wildlife research as habitat studies vary widely in scope and scale of interest, but our systematic review data may offer some insight.

In relation to Fig. 5, a higher ratio of aircraft- to satellite-based habitat sensing records could be interpreted to indicate an overall tendency for habitat studies to require finer-scale data. As might be expected, the ratio was generally higher for smaller animals (e.g. small birds and mammals) compared to larger animals (e.g. large mammalian herbivores and carnivores), however it is interesting that the ratio for raptors was nearly as high as small birds, indicating that there are factors at play beyond animal size. For example, both raptor- and small bird-related records commonly included "nest-centric" studies involving characterization of habitat within a relatively close vicinity of individual nests and requiring fine-scale and timely data to do so (e.g. McConnell et al. 2008, Broughton et al. 2012). Many records involved habitat characterization throughout home ranges of individually tracked animals, and in these cases there was a tendency to shift from aircraft- to satellite-derived data with larger home range size. Mammalian carnivores and large herbivores, for example, tend to occupy relatively large home ranges. Other records involved extrapolation of habitat models developed in local studies to much larger areas in order to estimate the amount of suitable habitat available to species, and in these cases satellite-derived data were usually used.

Overall, we believe that small UAS will prove useful for habitat sensing throughout the field of wildlife research whenever there is a need to collect very fine-scale (<20 cm/pixel) data in a timely fashion in areas that would otherwise be laborious or impractical to survey on the ground. Such cases will likely tend to involve smaller animals from all three major groups and more rarely involve larger, wider-ranging animals such as large terrestrial mammals and marine mammals. Prime examples are provided by Rodriguez et al. (2012) and Chabot and Bird (2013). The former used a small autonomous UAS to conveniently and precisely retrace foraging flights averaging 14 km in length by the small Lesser kestrel in order to obtain timely high-resolution (8 cm/pixel) imagery of preferred foraging habitats. The latter programmed a UAS to capture 9-cm/pixel imagery of a dense 128-ha emergent wetland impoundment that is impractical to survey at ground level in order to detect areas of finely interspersed water and vegetation that attract breeding Least bitterns, a small and highly secretive heron species. While the above studies used consumer-grade cameras for imaging, small UAS can also carry multispectral or infrared cameras for more advanced vegetation sensing (Berni et al. 2009, Laliberte et al. 2011b, McGwire et al. 2013, Knoth et al. 2013) as well as lidar for fine-scale vertical vegetation structure and topographical sensing (Lin et al. 2011, Wallace et al. 2012, Chisholm et al. 2013).

Telemetry tracking

Use of electronic animal tracking devices is widespread throughout the field of wildlife research and management, as evidenced by the large number and diversity of relevant records we uncovered, with telemetry tracking performed on animals ranging in size from amphibians and hummingbirds to elephants and whales. Once UAS-based automated radio tracking becomes possible, we again might expect it to be particularly useful at intermediate spatial scales between ground-based tracking (typically performed on foot or by vehicle) and conventional aerial telemetry. We suspect that explicit mention of aerial telemetry is greatly underreported in primary literature record summaries since it is a well-established technique that is likely considered a given when it comes to large, wide-ranging animals. Nevertheless, the aerial telemetry records we found revealed a prevalence of cases involving relatively large waterbirds and large mammalian terrestrial herbivores and carnivores (Fig. 6). Particularly large, far-travelling species are more frequently tracked by satellite uplink, as was seen with large migrating wading birds, raptors and waterfowl, some larger mammalian herbivores and carnivores, marine mammals and sea turtles.

Similar to habitat sensing, the frequency ratio of larger satellite-GPS- to smaller radio-logger-based devices within groups of animals shown in Fig. 7 could be considered an indicator of which species tend to require smaller-scale tracking for which UAS could be useful. Certainly there is no use considering small UAS for long-distance migration path studies and they can probably be ruled out for larger terrestrial mammals as well as marine mammals, with the possible exception of short-distance movements of pinnipeds around breeding colonies. They will more likely be advantageous for animals with small to medium home ranges, such as small birds, landfowl, small mammalian carnivores (e.g. mustelids), small mammals, bats, primates, and many small reptiles (e.g. land turtles and snakes that are often laboriously tracked on foot through rugged terrains). Among waterbirds, they may be useful for tracking small seabirds around breeding colonies as well as shorebirds, and they might be used to track local movements of raptors and waterfowl. Ground-based tracking will, however, remain the best option for animals occupying very small ranges, such as amphibians and certain small birds and mammals.

When it comes to wildlife tracking, practitioners should always carefully consider the wide variety of available options. A recent review of these with emphasis on costs and technical limitations is provided by Thomas et al. (2011). As mobile phone network coverage continues to expand, relatively compact and low-cost GPS-GSM transmitters promise to become a most convenient option for automated wildlife tracking. However, they will remain impractical in very remote areas lacking network coverage, for animals that spend a lot of time in GPS-impeded areas such as dense forests and dens, and for very small species (<700 g).

Conclusion

In summary, burgeoning small UAS technology is likely to make numerous contributions to wildlife research and management in the near future. In some cases they will prove to be superior substitutes for conventional aircraft, in others they will take over tasks that would otherwise be carried out on the ground, and in others still they may open entirely novel avenues for studying and managing wildlife. Fixed-wing models will be useful for performing precise, low-disturbance surveys of animals that congregate in predictable locations or otherwise occur in relatively high densities over small areas, while rotary-wing models will be useful for up-close surveys and observation of animals in hard-to-reach places likes trees, cliffs and certain manmade structures. Small UAS will be beneficial for wildlife habitat sensing in situations where timely, fine-scale data are required in areas where ground-based data collection would be laborious or impractical. Upcoming UAS-based automated telemetry tracking will be useful for tracking animals that occupy small to medium ranges, particularly in rugged, unnavigable or GPS-impeded habitats.

Finally, prospective users should be aware of local regulations relating to the operation of UAS, which are often viewed as restrictive or prohibitive in most developed countries. For example, it is commonly forbidden to fly UAS beyond direct visual range of the ground crew except in very remote areas, and applying for permits to operate UAS can be a lengthy and exacting process. These challenges are discussed in further detail by Dalamagkidis et al. (2008), Rango and Laliberte (2010) and Mulac (2011). However, many governments are currently working on plans to facilitate the integration of small UAS into the airspace system, acknowledging the imminent proliferation of the technology. For example, the recently adopted *FAA Modernization and Reform Act of 2012* calls for new regulations to this effect to be put in place in the United States by 2015 (Mica 2012), and Transport Canada is poised to announce less restrictive regulations for UAS under 25 kg in 2014.

Acknowledgements

We thank M. Humphries for helping to conceptualize this review and for initial guidance with the systematic literature review process, and J. Brammer and C. Miller for helping to compile the list of reviewed publications.

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Table 1. List of terms used to search wildlife-related publications indexed in the Web of Science for records alluding to use of aircraft, satellites or electronic animal tracking devices.

Search terms	Search terms (continued)
aerial	lidar
air photo, airphoto*, air survey*	*logger*
airborne	modis
aircraft	national wetlands inventory
airplane*	normalized difference, NDVI, NDSI, NDWI
airship*	orbview
argos	orthophoto*, ortho photo*, ortho imag*
aster	plane*
blimp*	quickbird
cessna*	radio*
digital elevation model*, DEM	remote* sens*
digital surface model*, DSM	rotary wing
digital terrain model*, DTM	satellite
fixed wing	single engine
geolocat*	shuttle radar, SRTM
geoeye	spaceborne, SIR
global positioning, GPS	synthetic aperture radar, SAR
google earth	*telemetr*
helicopter*	thermal camera*, thermal imag*, thermal sens*
infrared, FLIR	transmitter*, PTT*, VIT*
ikonos	twin engine
land cover, landcover	very high frequency, VHF
landsat	worldview

Table 2. List of wildlife-related publications indexed in the Web of Science that were searched for records alluding to use of aircraft, satellites or electronic animal tracking devices.

Publication	Records*	Publication (continued)	Records*
Wildlife publications		*Mammal publications*	
European Journal of Wildlife Research	975	Acta Chiropterologica	482
Journal of Fish and Wildlife Management	112	Alces	42
Journal of Wildlife Management	2,564	American Journal of Primatology	3,354
South African Journal of Wildlife Research	320	Aquatic Mammals	170
Wildlife Biology	609	Australian Mammalogy	71
Wildlife Monographs	40	Folia Primatologica	2,014
Wildlife Research	1,069	Hystrix Italian Journal of Mammalogy	143
Wildlife Society Bulletin	1,237	International Journal of Primatology	1,026
Wildlife total	*6,926*	Journal of Mammalogy	1,864
		Mammal Review	275
Bird publications		Mammal Study	160
Acta Ornithologica	260	Mammalia	730
Ardea	524	Mammalian Biology	787
Ardeola	335	Marine Mammal Science	1,035
Auk	1,638	Primates	607
Avian Biology Research	303	Ursus	286
Avian Conservation and Ecology	123	*Mammal total*	*12,760*
Bird Conservation International	463		
Bird Study	620	*Herptile publications*	
Condor	1,352	Acta Herpetologica	144
Emu	632	African Journal of Herpetology	126
Ibis	1,397	Amphibia-Reptilia	835
Journal of Avian Biology	1,034	Applied Herpetology	67
Journal of Field Ornithology	731	Asian Herpetological Research	106
Journal of Ornithology	2,204	Chelonian Conservation and Biology	358
Journal of Raptor Research	850	Copeia	1,386
Ornis Fennica	298	Herpetologica	630
Ornithological Science	62	Herpetological Conservation and Biology	293
Ornitologia Neotropical	616	Herpetological Journal	470
Ostrich	787	Herpetological Monographs	85
Revista Brasileira de Ornitologia	400	Herpetozoa	97
Waterbirds	1,119	Journal of Herpetology	1,304
Wilson Journal of Ornithology	1,373	Salamandra	115
Bird total	*17,121*	South American Journal of Herpetology	9
		Herptile total	*6,025*

* Total records indexed since the year 2000, as of 10 November 2013

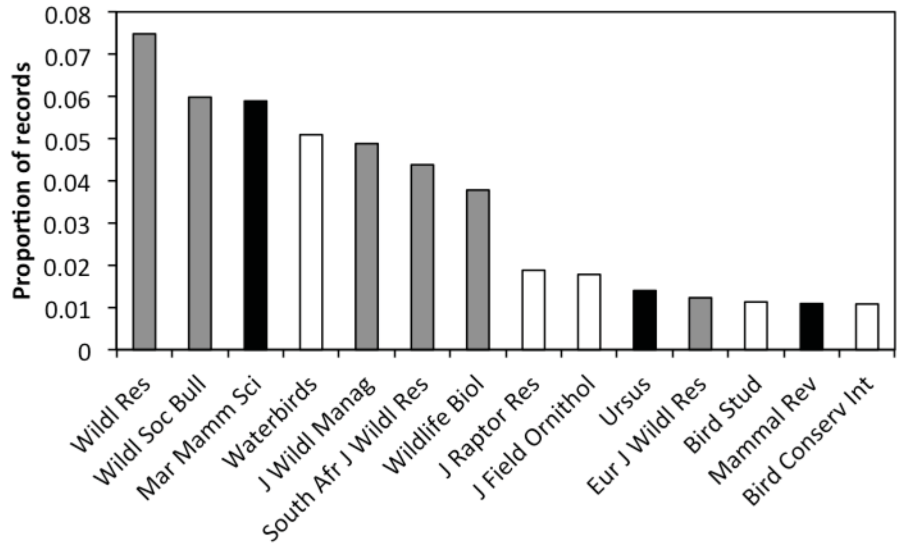

Figure 1. Wildlife-related publications (min. 200 indexed records) with the most frequent relative occurrence of records alluding to use of aircraft. Grey bars represent general wildlife publications, black bars represent mammal-specific publications and white bars represent bird-specific publications.

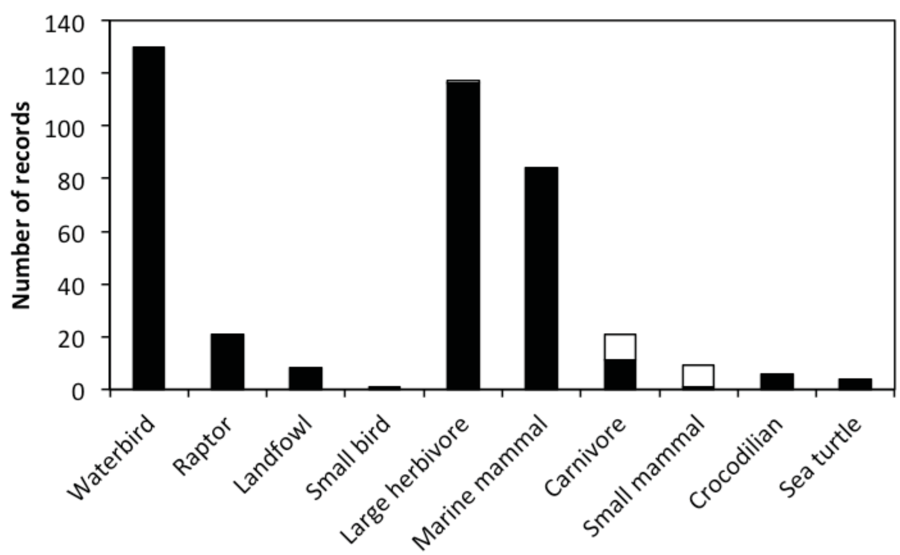

Figure 2. Total number of records alluding to aerial visual observation by category of animal. White portions of bars represent cases of indirect observation, such as animal tracks or burrows.

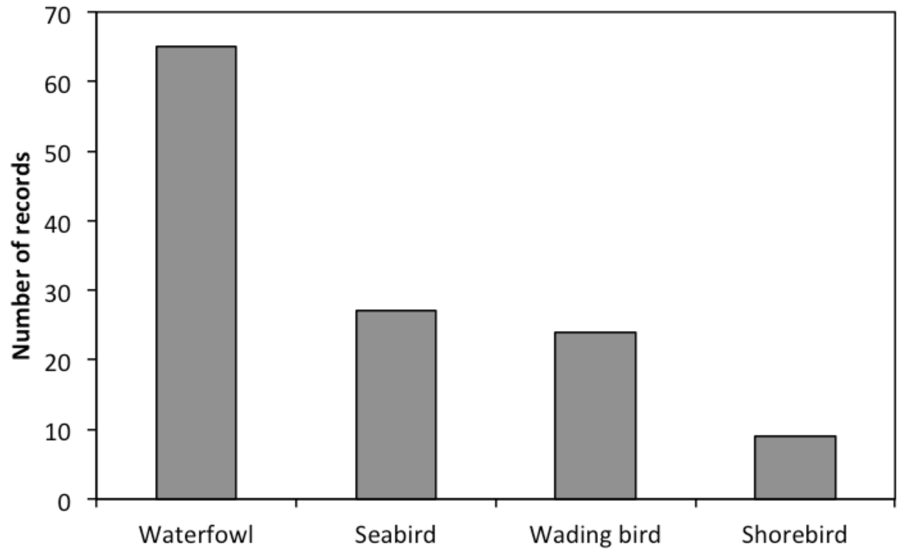

Figure 3. Total number of records alluding to aerial visual observation by category of waterbird.

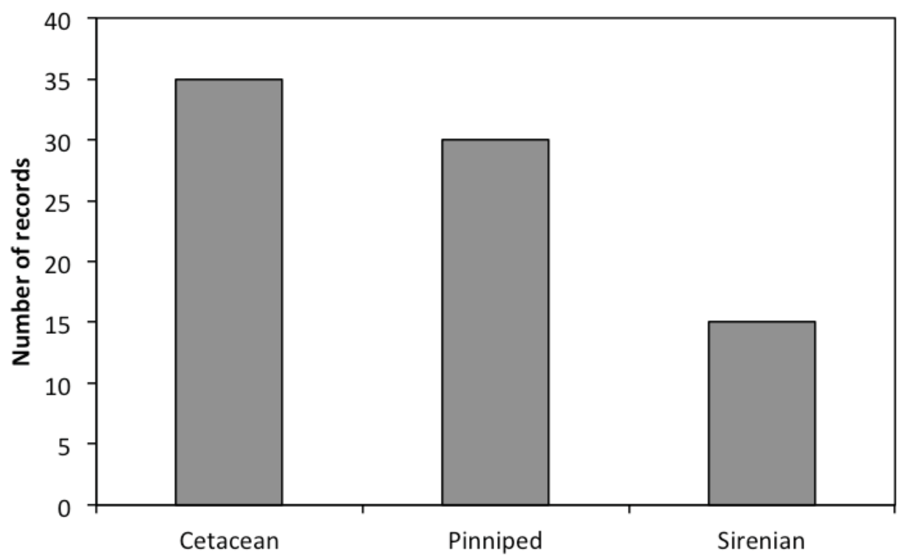

Figure 4. Total number of records alluding to aerial visual observation by category of marine mammal.

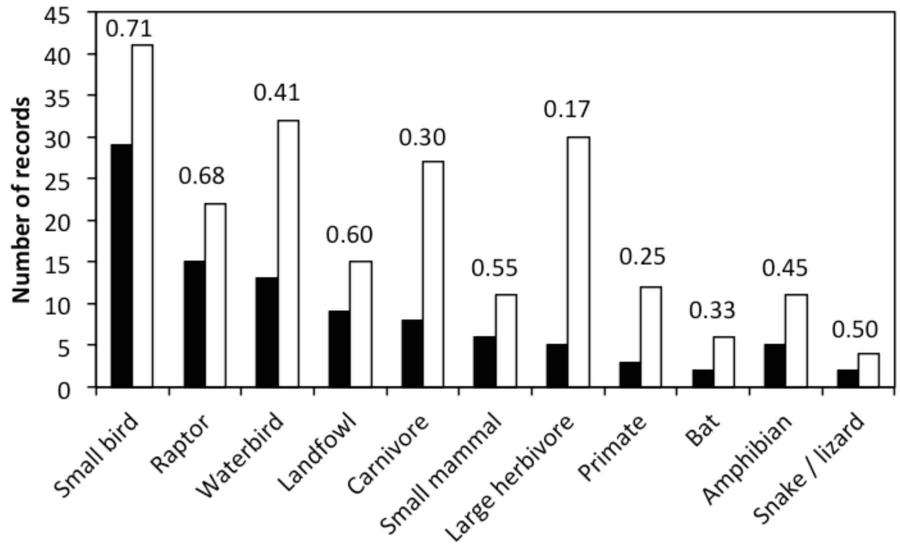

Figure 5. Total number of records alluding to aircraft-based (black bars) and satellite-based (white bars) habitat sensing by category of animal. Numbers represent the ratio of aircraft- to satellite-based records.

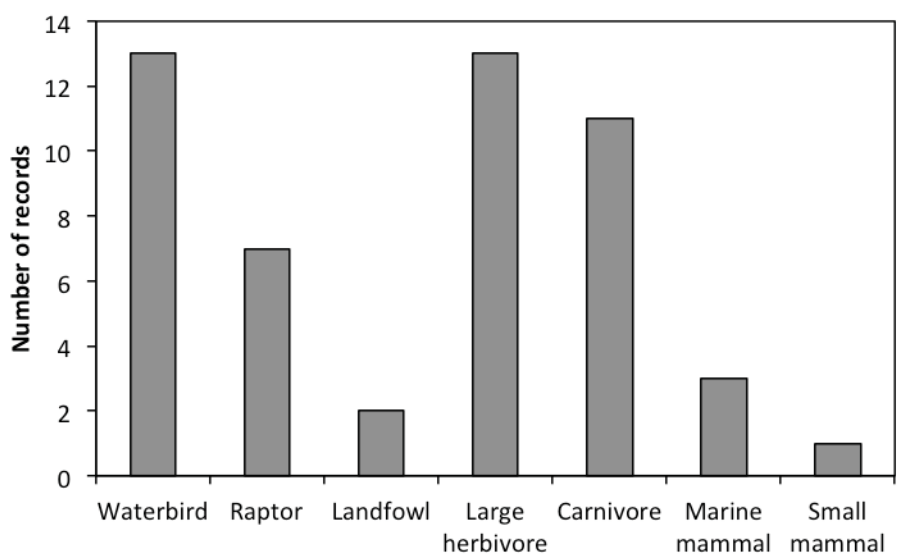

Figure 6. Total number of records alluding to aerial telemetry by category of animal.

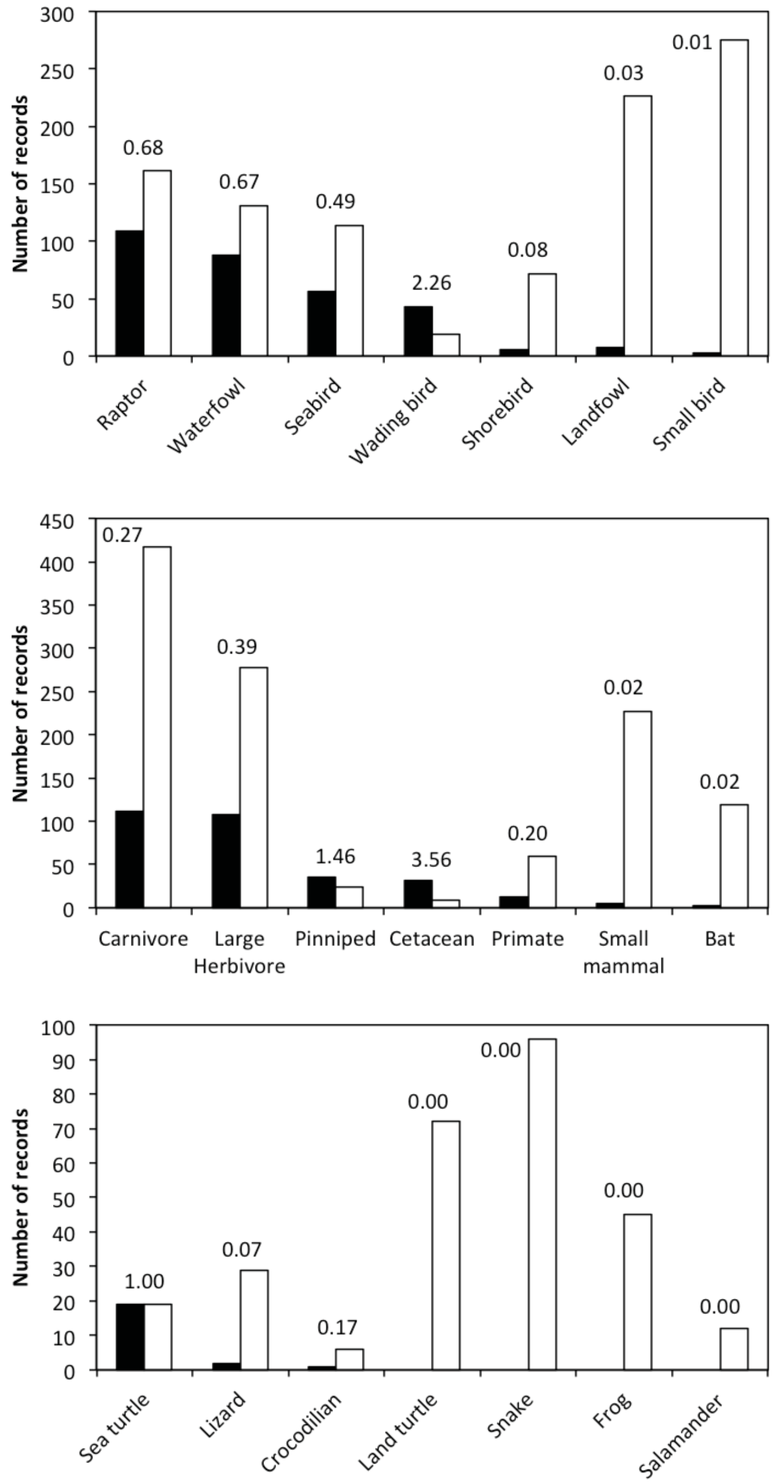

Figure 7. Total number of records alluding to use of electronic tracking devices (black bars = satellite-GPS devices; white bars = radio-logger devices) by category of bird (top), mammal (middle) and herptile (bottom). Numbers represent the ratio of satellite-GPS- to radio-logger-device records.

CONNECTING STATEMENT

Having reviewed potential applications for UAS in wildlife science, the remainder of the thesis is focused on case studies conducted in the field concerning two waterbird species, the least bittern and the common tern. The following chapter, the first of two concerning the least bittern, presents a method evaluation/validation study on the use of a small UAS for fine-scale mapping of the species’ wetland habitat. It also serves as a general introduction to the materials and methods used throughout the case studies.

CHAPTER 2

SMALL UNMANNED AIRCRAFT: PRECISE AND CONVENIENT NEW TOOLS FOR SURVEYING WETLANDS

Abstract

Unmanned aircraft systems (UAS) could be of benefit for surveying wetlands, which often have spatially complex habitats that are challenging to navigate and assess at ground level. We used a small UAS to acquire aerial imagery and characterize land cover in a 128 ha wetland impoundment as part of a conservation study of the least bittern (*Ixobrychus exilis*). The method was successful in gathering sub-decimetre georeferenced imagery that clearly revealed the fine-scale water–vegetation interface and in which several types of vegetation could be distinguished and classified using spectral image analysis software. Simplified three-category land cover classifications obtained in this manner showed strong agreement with manual classification of random points in the imagery, as evidenced by a kappa coefficient of 87.19% (n = 600). Compared to cover estimates made during concurrent ground-based surveys in 30 sampling plots, UAS data yielded overall similar water-vegetation ratios, but proved more effectual for detecting small amounts of highly interspersed water. Significant differences (p = 0.004) in cover estimates of the dominant vegetation, cattail, were likely primarily due to limitations of ground-based surveys. Given the effective and convenient application of a UAS in this study, we recommend their further use in wetland-related research and management.

Introduction

Wetlands are tremendous reservoirs of plant and animal diversity as well as providers of numerous invaluable ecosystem services including water purification, sediment and nutrient retention, groundwater replenishment, shoreline stabilization, flood control, and storm protection. Unfortunately, degradation and loss of wetlands is currently proceeding at a faster rate than that of any other type of ecosystem and countless wetland-associated species consequently find themselves at risk (Millennium Ecosystem Assessment 2005). Effective conservation and management of wetlands depends on the ability to collect accurate and timely data on the habitats that comprise them (Finlayson and Mitchell 1999). However, wetlands tend to be challenging to survey because of their often complex patchwork of flooded areas interspersed with dense vegetation, which can be laborious to navigate and characterize at ground level. Alternatively, wetland habitat can be examined by means of aerial imagery acquired by satellite or aircraft, although constraints of these methods may include limited resolution, inflexible timing of data acquisition, and (or) high cost (Lee and Lunetta 1995; Adam et al. 2010).

In recent years there has been burgeoning use of small unmanned aircraft systems (UAS) for surveying and monitoring natural landscapes, namely forests and rangelands (Hardin and Jackson 2005; Dunford et al. 2009; Rango et al. 2009; Breckenridge and Dakins 2011; Getzin et al. 2012). Typically cited benefits of UAS for these applications include their ability to acquire aerial imagery at very high spatial resolution (<10 cm/pixel), to be deployed in a convenient, timely, and repeatable fashion, and to operate at a competitive cost. UAS may therefore be an attractive option for surveying the spatially complex and hard-to-navigate habitats characteristic of many wetlands.

Here we describe the application and performance of a basic “off-the-shelf” UAS that was used to acquire land cover data in a man-made wetland in the province of Quebec, Canada, for a broader study of the habitat ecology of a threatened wetland bird species, the least bittern (*Ixobrychus exilis*; Poole et al. 2009). The main motivation for employing a UAS was to precisely map the fine-scale water-vegetation interface, which is believed to influence habitat selection by nesting bitterns (Rehm and Baldassarre 2007; Moore et al. 2009; Darrah and

Krementz 2010). It was further hoped that major vegetation types used by bitterns for nesting would be distinguishable in the aerial imagery gathered by the UAS. Overall, the aim was to take advantage of a convenient and economical solution to supplement ground-based habitat surveys, as opposed to seeking first-rate remote sensing data. Land cover estimates made during concurrent ground-based surveys served as a basis for comparison with cover data derived from the UAS aerial imagery.

Methods

Study site and context

The study focused on a 128 ha wetland impoundment (Fig. 1) situated on Ministry of National Defence property in Baie-du-Febvre, Que. Managed by Ducks Unlimited Canada, the impoundment was built on former agricultural fields and flooded in 1988. It is partitioned into three basins separated by dykes: a large south basin and two smaller north-east and north-west basins, with canals running around the site's periphery and along one side of each transecting dyke. The impoundment has evolved into a thriving emergent herbaceous wetland dominated by cattail (*Typha latifolia* and *T. angustifolia*) and bur-reed (*Sparganium eurycarpum* and *S. emersum*), as well as smaller amounts of sedges (*Carex stricta* and *C. comosa*), wild rice (*Zizania aquatica*), flowering rush (*Butomus umbellatus*), arrowhead (*Sagittaria latifolia* and *S. rigida*), and a single shrub species, buttonbush (*Cephalanthus occidentalis*). Invasive reed canary grass (*Phalaris arundinacea*) grows along the dykes and outer margins of the wetland. Numerous species of floating vegetation occur in areas of standing water.

Over time the impoundment has become a site of high conservation interest, in particular because of its sizable breeding population of least bitterns, a threatened species of small, secretive herons first detected in the wetland in 1994. Since 2004, the site's bittern population has been the focus of research by the Canadian Wildlife Service (CWS; Jobin et al. 2007; 2009), although the largely ground-based investigations to date have yet to definitively identify which habitat parameters explain the bird's distribution within the wetland. With the site having now been designated as critical habitat in the national least bittern recovery strategy under the Species at Risk Act (Environment Canada 2011), it has become imperative to elucidate the bittern's habitat relationships to develop a management plan.

Ground-based data collection

Ground-based data collection (Gilbert 2011) was carried out from 7–21 September, 2011, following a standard protocol developed by the CWS over the course of an extensive study of the wetland from 2004 to 2006 (Jobin et al. 2007). Habitat was surveyed at 30 sampling points (Fig. 1) where least bittern surveys had previously been conducted. For each point situated in the interior of the wetland (15 total), land cover was surveyed in a 25 m radius circular plot using visual observations and line–intercept sampling (Bonham 2013). Transitions in dominant cover were noted along four transects in each cardinal direction from the centre of the plot. For each of the 15 remaining sampling points situated along the periphery of the wetland, along the dykes separating the three basins or at the edge of large expanses of standing water, a half-circle plot was sampled rather than a full circle. In this case, cover transitions were noted along three 25 m transects: two diagonal transects at a 45° angle on either side of a central transect (perpendicular to the edge). Transition data and visual observations were then used to produce a sketch of each plot, from which total per cent coverage by each cover class was estimated. Cover patches in the sketches were for the most part classified as the single most dominant class, however on occasion patches were noted as being comprised of two classes when neither appeared to be clearly dominant. In these cases, each class was attributed half of the patch area when estimating total cover in the plot.

UAS and aerial data collection

Aerial imagery of the wetland was gathered with the AI-multi fixed-wing UAS (Aerial Insight, Brandon, Man.), shown in Fig. 2. The 2.1 m wingspan, ~4 kg electric aircraft is equipped with the MP2028g autopilot system (MicroPilot, Stony Mountain, Man.), which executes preprogrammed waypoint flights by integrating data from a GPS receiver, pressure altimeter, pitot tube, and miniature accelerometer–gyro system. The modular airframe is comprised of a carbon fibre fuselage and fibreglass wings and V-tail. Control surfaces include ailerons, flaps, and ruddervators. A compact digital camera (in this case, a 10 megapixel Canon S90) is housed in a gyro-stabilized mount protruding from the side of the fuselage, under the wing. The aircraft is hand-launched and typically remains in autonomous mode all the way through to landing, which is performed on its belly on a vegetated surface. However, the aircraft can be switched into manual radio-control mode at any time, for example, to perform precision landings in tight spaces. While in flight, a radio link keeps the aircraft in communication with a laptop-based ground control station (shown in Fig. 2a) where flight status information is displayed via MicroPilot's Horizon "moving-map" software (Fig. 3). Commands can also be transmitted to the aircraft in real time, for example, an abort-mission sequence. Flights can last up to an hour at a cruising airspeed of ~60 km/h using a single 11 000 mAh lithium-polymer rechargeable battery pack. To cover large areas, it is often prudent to plan multiple flights, replacing the battery between each. The aircraft cannot operate in precipitation or winds >30 km/h.

Prior to the aerial survey, eight "safety orange" plastic cones were placed around the dykes and periphery of the wetland (Fig. 1) to serve as control points to validate the georeferencing of the aerial imagery. Their locations were recorded with a Garmin handheld GPS. The survey was then conducted on 27 July, 2011, deploying the aircraft from a field adjacent to the wetland. The site was covered in two successive flights carried out between 1015 and 1420 at an altitude of 274 m (900 ft) AGL, each consisting of a series of back-and-forth transects (trajectory of first flight shown in Fig. 3) during which the camera acquired overlapping JPEG photos. The resulting 220 photos were geotagged, orthorectified, and stitched together into a single georeferenced TIFF image of the entire wetland by Pix4D (Lausanne, Switzerland) using a process wherein the aircraft's positional and attitudinal data corresponding to each photo are retrieved from the autopilot's flight log.

Aerial image classification and analysis

The finalized aerial image of the wetland was loaded into ArcMap (Esri ArcGIS v.10.1 Advanced License, Redlands, Calif.) and analysed using the spatial analyst extension. Fifty metre radius circular plots centred on each of the 30 sampling points were extracted from the larger image and supervised classification of land cover was performed in each plot. Identification of cover classes, namely vegetation types, was aided by the sketches and raw data from ground surveys, a coarse-scale sketch of vegetation layout over the entire wetland produced following an aerial survey in 2006 (Jobin et al. 2007), and consultation with CWS biologists familiar with the site. In each plot, a series of polygons were manually drawn as representative "training samples" to generate spectral signatures for the different cover classes. The maximum likelihood classification process was then used to automatically classify the entire plot into the predefined set of classes. Training samples were often tweaked one or more times following an initial run to improve results. To reduce processing complexity, classification was carried out in two stages. First, plots were classified into water, floating vegetation, and emergent vegetation. Areas of water and floating vegetation were then subtracted from the original images and the remaining areas of emergent vegetation were further classified, with the primary aim of partitioning cattail from the other types of vegetation. Following each stage of classification, the majority filter and boundary clean tools were used to reduce noise and smooth out the classified images, after which all patches <0.25 m^2 were subsumed into surrounding patches using the region group, set null, and nibble tools. When partitioning floating and emergent vegetation, the latter three tools were also occasionally used to manually correct evident misclassifications resulting from overlap in spectral signatures. Finally, the con tool was used to replace the areas of emergent vegetation from the first classification stage with the further classified images from the second stage. For comparison with ground survey data, the 25 m radius circular and half-circular areas corresponding to the ground sampling plots were extracted from the larger 50 m radius plots. Per cent cover by class was calculated in each plot with FRAGSTATS (McGarigal and Marks 1995) via the Patch Analyst (v.5.1, Ontario Ministry of Natural Resources, Thunder Bay, Ont.) extension for ArcGIS. Total edge density and edge density by class were also calculated as a proxy for the degree of interspersion (i.e., spatial heterogeneity) within plots.

To evaluate the automatic classification of the aerial imagery in relation to manual appraisal, 20 randomly placed points were generated in each plot, for a total of 600 points across all plots. Land cover at each point was manually classified into one of three main categories: water (including floating vegetation), cattail, or other. The manual classification was then contrasted with the automatic classification for each point, and a global kappa coefficient of agreement (κ) was calculated according to the equation:

$$\kappa = \frac{P_o - P_c}{1 - P_c}$$

where P_o was the observed proportion of points for which manual and automatic classification were in agreement, and P_c was the proportion of points for which agreement would be expected by chance based on the observed frequencies of the cover classes. The κ threshold for "strong" agreement is commonly considered to be 80% (Sim and Wright 2005; Luscier et al. 2006).

Statistical analyses

Statistical tests were performed with SPSS Statistics (v.21.0, IBM Corp., Armonk, N.Y.) using a significance level of 0.05. Kolmogorov-Smirnov tests were first used to verify the distribution of all variables and subsequent procedures were chosen accordingly. With regard to manual versus automatic classification of aerial imagery, it was hypothesized that an increasing degree of class interspersion (i.e., spatial heterogeneity) may increase disagreement due to the difficulty of interpreting complex mosaics of land cover. To test this, Spearman's rank correlation coefficient was used to compare per cent agreement between classification methods in sampling plots to total edge density. In addition, the proportion of points classified into each of the three classes by manual versus automatic classification were compared across plots using paired-sample t-tests. Finally, paired-sample t-tests were also used to compare per cent cover estimates in plots from ground-based surveys to those from the aerial survey for each cover class, again considering water/floating vegetation, cattail, and other.

Results

The final unified aerial image of the wetland produced by the UAS survey, featured in Fig. 1, has a spatial resolution of 8.8 cm/pixel. The mean distance between the locations of the control cones as they appear in the imagery and their recorded coordinates is 4.2 m (range = 2.9–5.4 m), which is comparable to the error of the handheld GPS and therefore indicates that the use of flight log data to georeference the imagery yielded accurate results.

Aerial image classification

Water was easily distinguishable from all other cover types, though its reflectance varied considerably throughout the imagery. Floating vegetation was also readily distinguishable by its distinctly bright hues and smooth texture. Emergent vegetation was relatively more challenging to classify, although cattail generally stood out because of its distinctly coarse texture and dull olive brown to olive grey hues compared to the deeper or more vivid green hues of other vegetation types. The second most prevalent genus of emergent vegetation, bur-reed, was often distinguishable, as were other common species and genera including canary grass, wild rice, sedges and buttonbush (Table 1), however in numerous sampling plots they proved difficult to adequately distinguish from each other or from various other non-cattail vegetation using the maximum likelihood classification process, and in some cases even manually. For the purpose of subsequent comparative analyses, it was therefore deemed practical to combine them into a single "other" class.

Agreement between manual and automatic classification of random points in sampling plots was generally high, averaging 91.5% (P_o), with no less than 80% (16/20 points) agreement in any single plot (Table 1). Within the observed 80%–100% agreement range, however, there was a significant negative correlation with total edge density (r_s = -0.573, p = 0.001). Overall, 29.33%, 34.83%, and 35.83% of points were manually classified into water, cattail and other, respectively; compared with 28.17%, 37.50%, and 34.33%, respectively, by automatic classification. The difference between classification methods was statistically significant for cattail (t = -2.112, p = 0.043) but not for water (t = 1.651, p = 0.109) or other (t = 1.224, p = 0.231). Based on the observed class frequencies by each method, the rate of agreement expected by chance (P_c) was 33.63%, whereas P_o = 91.5%, which results in κ = 87.19%, thus indicating "strong" overall agreement between manual and automatic classification.

Comparison of ground-based and aerial land cover estimates

Summary land cover data for sampling plots are shown in Table 1. Mean water cover (including floating vegetation) across all plots estimated from the ground exceeded water cover estimated from aerial imagery by only 0.55 percentage points, which was not statistically significant (t = -0.278, p = 0.783). However, ground estimates of cattail cover were overall significantly higher than aerial estimates (t = -3.126, p = 0.004) while ground estimates of other cover were significantly lower than aerial estimates (t = 2.880, p = 0.007). Examining discrepancies in cover estimates at the level of individual plots revealed several apparent patterns. Although water cover estimates did not globally differ between ground and aerial survey methods, there was a tendency for ground estimates to exceed aerial estimates in plots (e.g., 3, 4, 8, 18, 23, and 28) containing relatively large, homogeneous expanses (i.e., a single large patch) of water. Conversely, ground estimates of water cover tended to be smaller (in some cases virtually nil) in plots (e.g., 5, 22, and 29) containing a relatively small amount of highly interspersed water (high water edge density relative to total area), as exemplified in Fig. 4. Finally, ground estimates of water cover were smaller in all three plots where emergent vegetation was dominated by bur-reed and contained little to no cattail (20, 24, and 25). With regard to cattail cover, there appeared to be two main factors that accounted for its general overestimation in ground surveys compared to aerial imagery. In several plots (e.g., 5, 6, 8, 9, 22, 29, and 30), large expanses of relatively sparse but dominant cattail interspersed with many small patches of water or other vegetation were generalized in ground surveys as being entirely composed of cattail (e.g., Fig. 4). In addition, canary grass growing along the margins and dykes of the wetland tends to blend into cattail, and in several plots containing such transition areas (e.g., 2, 13, 18, and 21) ground surveys had a greater tendency to generalize them as cattail than did aerial image classification.

Discussion

Wetland research and management may benefit from the convenient and high-resolution aerial imaging capabilities of small UAS. The AI-multi UAS employed in this study successfully gathered sub-decimetre georeferenced aerial imagery of a relatively large and spatially complex emergent wetland. The primary aim of mapping the fine-scale water–vegetation interface was achieved, as areas of standing water and floating vegetation were clearly distinguishable from emergent vegetation in the imagery. Furthermore, major types of emergent vegetation were generally distinguishable, particularly cattail, which is known to be one of the least bittern's preferred nesting habitats in its northern range (Post and Seals 1993; Bogner and Baldassarre 2002; Jobin et al. 2011). Several other types of vegetation, while manually distinguishable, frequently proved impossible to adequately sort out in the automatic image classification process, presumably because of excessive overlap in their spectral properties. This is a limitation of ArcGIS's image classification tools that could potentially be overcome by using object-based image processing software capable of analysing texture in addition to colour, such as Trimble eCognition (Luscier et al. 2006; Laliberte and Rango 2011). Resources permitting, use of multispectral or hyperspectral cameras can also improve the ability to distinguish vegetation (Adam et al. 2010).

When keeping to three basic land cover classes (water, cattail, and other), the automatic classification process proved reliable compared to manual classification of a sample of points in the imagery, with a global kappa coefficient of 87.19%, which takes into account the frequency of agreement expected purely by chance. As speculated, agreement tended to be lower in sampling plots containing a higher degree of class interspersion, making it more difficult to interpret land cover. Results also suggest that automatic classification had a slight tendency to overestimate cattail at the expense of both water and other vegetation.

It is noteworthy that for the purpose of this component of the broader study (relating bittern abundance in survey plots to habitat structure), supervised classification was performed in each plot individually to achieve the best possible results. Aerial imagery of the wetland was gathered by the UAS over the course of two flights spanning about three hours, during which there were changes in sky conditions (e.g., brightness and cloud cover). This resulted in some noticeable inconsistencies in the unified image of the wetland, in particular variation in the reflectance of water and vividness of vegetation colours. Consequently, producing an adequate classified image of the entire site—as opposed to a series of small, separate samples—may prove more challenging.

The UAS survey yielded overall similar estimates of total water cover in sampling plots to ground- based surveys, but tended to produce higher estimates in plots where water was highly interspersed throughout the vegetation and lower estimates in plots where water was concentrated in large expanses. Higher estimates of water in three bur-reed-dominated plots containing little or no cattail could be due to expansion of bur-reed stands between the aerial survey in late July and ground surveys in September. Although cover data obtained with the UAS are certainly not fully accurate, they are likely closer to the “truth” than data gathered on the ground. Inaccuracies in cover estimates from ground-based surveys are to be expected due to the inherent difficulty of assessing and navigating through the dense and complex habitat of the wetland. Overestimation of cattail in particular is unsurprising because it tends to be the thickest and tallest of all vegetation types, commonly reaching over two metres in height by September when surveys were carried out. Small patches of water or other vegetation within cattail stands therefore tend be overlooked. Given the role of cattail in least bittern nesting, the likely more accurate cover data provided by the UAS survey are a welcome contribution. Moreover, superior detection of interspersed water was the main reason for employing the UAS in the study.

A final point to highlight regarding the use of the UAS to map land cover compared to ground surveys is the substantial reduction in time and effort required in the field. Whereas it took five days of physically strenuous work on the ground to survey a total area representing only a small fraction of the wetland, acquiring high-resolution aerial imagery of the entire site with the UAS was accomplished in one day without any physical exertion or intrusion into the wetland. The AI-multi UAS and necessary accessories can be purchased for roughly $20 000 and with proper use and maintenance can complete up to several hundred flights at relatively little additional cost, making it a reasonably economical option.

It is important to note that airspace regulations in most developed countries currently impose significant and often prohibitive restrictions on UAS use. For example, Transport Canada generally requires a minimum of two personnel to operate a small UAS such as the AI-multi as well as generous liability insurance coverage, and except in very remote locations will not permit operation of the air- craft beyond visual range of the ground crew. Operators must apply for a Special Flight Operation Certificate (SFOC) for each UAS mission, which can be a lengthy and exacting exercise requiring a detailed description of system specifications, operation procedures, flight plans, and safety considerations. However, regulations pertaining to UAS have begun evolving at a rapid pace as governments are increasingly recognizing the inevitable proliferation of the technology. These matters are further discussed by Dalamagkidis et al. (2008) and Rango and Laliberte (2010).

As UAS continue to become more widespread and accessible for civilian applications, they are expected to play increasingly frequent and varied roles in biological research, management, and conservation (Watts et al. 2010; Koh and Wich 2012; Anderson and Gaston 2013). In light of this study, we recommend their further use to improve and facilitate wetland-related endeavours.

Acknowledgements

We thank V. Carignan for general project coordination and assistance, H. Gilbert and A. Lachance for ground survey and data compilation assistance, G. Maillet for UAS survey assistance, G. Lewis for image processing assistance, B. Jobin and L. Robillard for vegetation identification assistance, and K. Panchuk for access to study site property. Funding and in-kind were provided by the Kenneth M. Molson Foundation, Environment Canada, the Canadian Wildlife Federation, Pix4D, Aerial Insight, MicroPilot, and the Fonds Québécois de la Recherche sur la Nature et les Technologies.

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Table 1. Summary data for ground-based and UAS aerial estimates of ground cover, other species identified in aerial imagery, edge densities derived from aerial imagery, and agreement between manual and automatic classification of random points in aerial imagery, in sampling plots surveyed in the wetland impoundment of Baie-du-febvre, QC, 2011.

Plot	% water (ground)	% water (aerial)	% *Typha* (ground)	% *Typha* (aerial)	% other (ground)	% other (aerial)	Other spp.*	Total edge (m/ha)	Water edge (m/ha)	*Typha* edge (m/ha)	Other edge (m/ha)	Class. agree. (%)
1	41.22	35.94	58.78	56.77	0.00	7.29	*S, P*	4914.42	3582.40	4791.85	1454.59	95
2	30.97	29.97	57.55	33.97	11.48	36.06	*S, P*	3279.86	1375.02	1904.84	3279.86	100
3	34.09	21.77	54.29	39.76	11.62	38.47	*S*	7543.16	1632.56	6507.70	6946.06	90
4	52.10	30.04	32.37	43.38	15.52	26.58	*P, S*	3733.51	1596.60	3075.93	2794.50	95
5	0.00	18.29	74.59	55.52	25.41	26.19	*S, Z*	8081.69	4930.11	6449.91	4783.37	90
6	7.01	3.36	92.99	67.95	0.00	28.69	*S*	6825.52	1193.36	5865.78	6591.90	90
7	6.78	1.01	93.22	85.62	0.00	13.37		3830.34	353.38	3476.96	3830.34	100
8	66.60	55.75	33.40	17.60	0.00	26.65	*S*	6219.54	3578.08	2730.39	6130.62	100
9	8.03	7.03	83.93	46.86	8.04	46.11	*S*	7419.53	1449.19	6186.33	7203.55	85
10	7.15	4.04	60.26	57.18	32.60	38.78	*S*	8110.73	1072.80	7667.90	7480.76	80
11	0.00	5.93	100.00	94.06	0.00	0.01		2396.46	2385.65	2396.46	10.81	90
12	27.36	19.76	0.00	0.00	72.64	80.24	*C, Co*	4269.35	4269.35	0.00	4269.35	95
13	10.72	10.92	89.28	54.74	0.00	34.34	*P, S*	3976.85	1904.13	3493.60	2555.97	95
14	0.00	3.41	28.91	20.61	71.09	75.98	*S, P*	4618.12	747.91	4473.04	4015.28	85
15	30.07	32.37	26.58	38.34	43.35	29.29	*S*	6054.41	2953.68	4937.53	4217.61	95
16	43.09	45.17	38.09	38.89	18.81	15.94	*S, P*	6309.72	3445.36	5898.34	3275.75	80
17	66.99	59.83	33.02	39.80	0.00	0.37		5162.21	4967.48	5136.07	220.88	90
18	59.03	42.51	40.97	42.78	0.00	14.70	*P*	2351.13	1049.76	2100.42	1552.09	100
19	19.72	22.53	29.32	29.52	50.97	47.95	*S*	10883.45	5168.57	6192.63	10405.71	85
20	75.37	89.06	0.00	5.07	24.63	5.86	*S, Z*	2943.16	2469.92	1798.19	1618.19	95
21	4.10	4.01	87.82	49.56	8.08	46.43	*P, S*	3459.70	942.00	3230.73	2746.66	95
22	0.00	10.19	58.29	46.65	41.71	43.16	*S*	10202.68	3156.78	7634.95	3156.78	90
23	72.42	52.62	17.53	22.30	10.05	25.08	*S, Z*	8160.74	5069.68	4524.31	6727.49	85
24	27.45	36.06	0.00	0.00	72.55	63.94	*S*	4179.22	4179.22	0.00	4179.22	95
25	23.77	50.79	0.00	0.00	76.23	49.21	*S, Z*	5012.07	5012.07	0.00	5012.07	100
26	8.13	11.90	0.00	0.00	91.87	88.10	*Z, S*	2347.94	2347.94	0.00	2347.94	100
27	5.89	7.08	65.09	64.97	29.03	27.95	*S, Z*	4833.83	1780.39	3944.09	3943.19	80
28	61.97	50.96	19.10	24.81	18.93	24.23	*C, S*	8765.09	5902.40	6704.44	4923.33	95
29	1.96	12.95	49.81	29.74	48.23	57.31	*S*	8871.36	3505.57	7555.98	6681.17	90
30	0.00	0.33	80.25	60.01	19.76	39.66	*S*	6632.82	183.77	6466.62	6615.26	80
Mean	*26.40*	*25.85*	*46.85*	*38.88*	*26.75*	*35.26*		*5712.95*	*2740.17*	*4171.50*	*4299.01*	*91.5*
SD	*25.23*	*22.15*	*31.70*	*24.43*	*27.49*	*22.33*		*2372.40*	*1649.11*	*2400.39*	*2368.91*	*6.6*

**S* = *Sparganium* spp.; *P* = *Phalaris arundinacea*; *Z* = *Zizania aquatica*; *C* = *Carex* spp.; *Co* = *Cephalanthus occidentalis*.

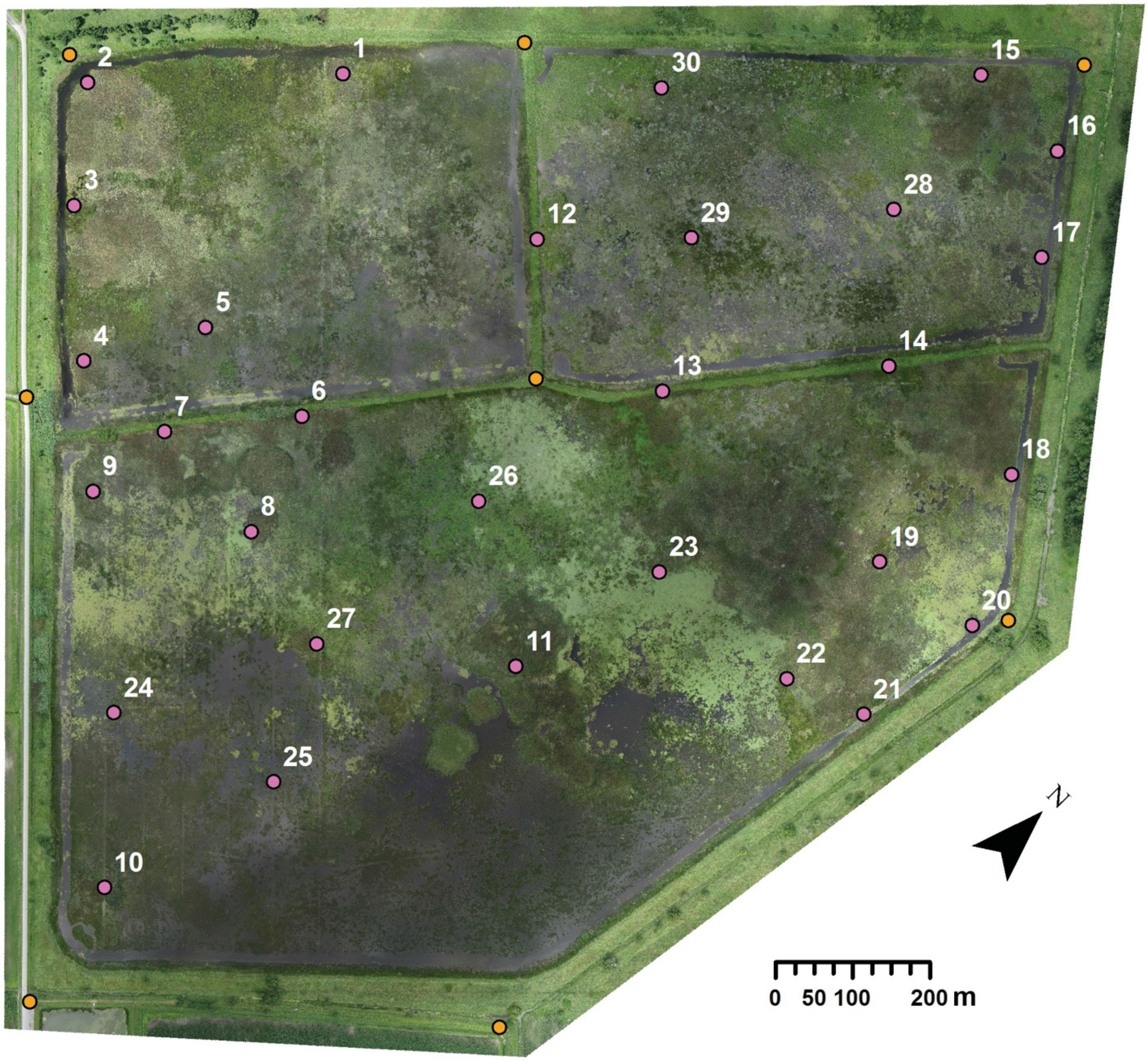

Figure 1. UAS aerial image of the Baie-du-Febvre wetland impoundment, Que., constructed from 220 overlapping photos with a spatial resolution of 8.8 cm/pixel. Orange dots indicate georeferencing control points. Pink dots and corresponding numbers indicate sampling plots.

Figure 2. The AI-multi UAS: aircraft and ground control station (above), and take-off (below).

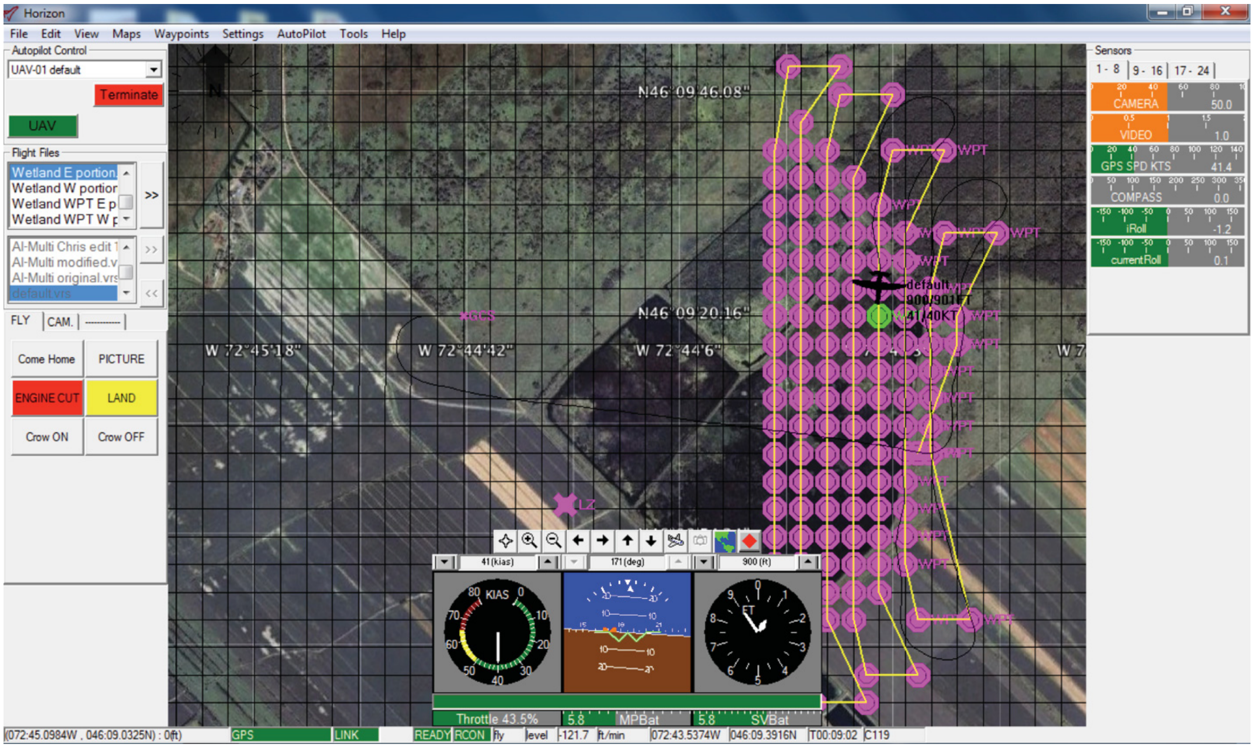

Figure 3. Screenshot of the MicroPilot Horizon UAS flight tracking interface displayed at the ground control station, showing the trajectory of the first of two flights over the Baie-du-Febvre wetland impoundment, Que.

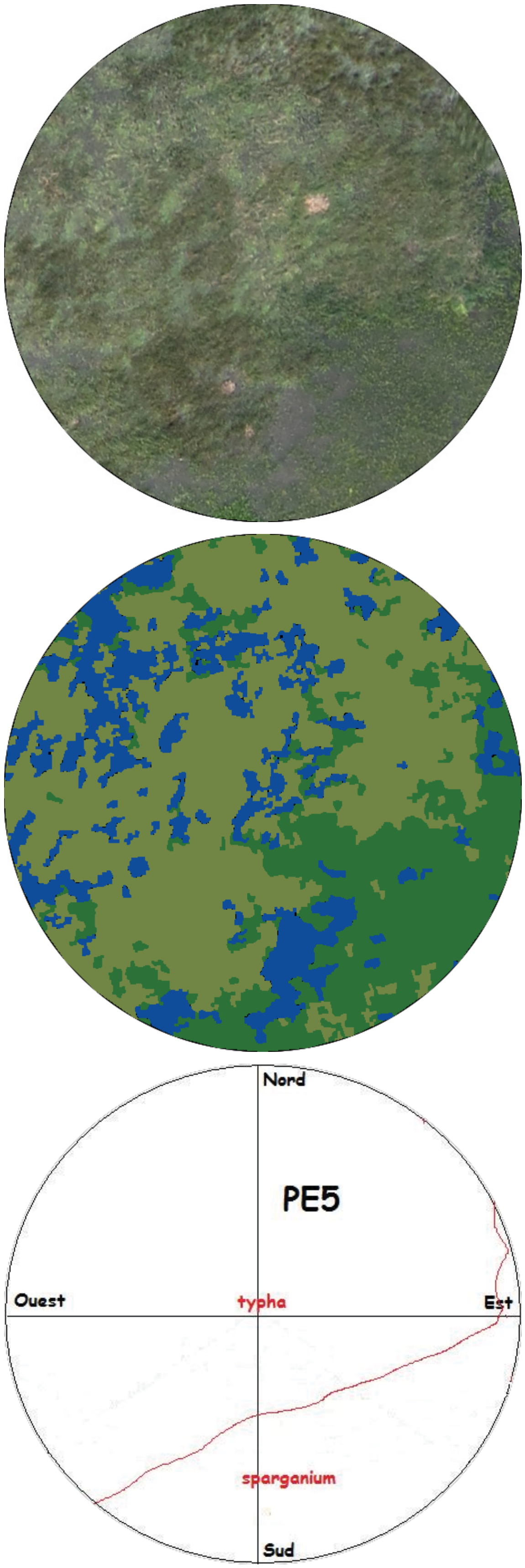

Figure 4. Example of detection in UAS aerial imagery, raw (above) and classified (middle), of highly interspersed water which went unrecorded in the ground survey (bottom). Blue areas in the classified image represent water (including floating vegetation), dull green areas represent cattail, and deep green areas represent other vegetation, in this case mainly bur-reed.

CONNECTING STATEMENT

Having detailed and validated the UAS-based method of collecting and analysing fine-scale wetland cover data, the following chapter applies this method in the context of a study of least bittern breeding habitat relationships that will ultimately help guide the creation of a wetland management plan.

CHAPTER 3

MEASURING HABITAT QUALITY FOR LEAST BITTERNS IN A CREATED WETLAND WITH USE OF A SMALL UNMANNED AIRCRAFT

Abstract

Created wetlands play an important role in the conservation of Least Bitterns (*Ixobrychus exilis*) by compensating for the loss of natural wetlands. In 2011, we studied habitat relationships of a major population breeding in a 128-ha cattail- and bur-reed-dominated impoundment in Quebec. We surveyed for bitterns and recorded habitat parameters at 30 points, making novel use of a small unmanned aircraft system (UAS) to obtain fine-scale land cover data. A model-selection approach based on Akaike's information criterion (AIC) determined that breeding density was best predicted by cattail cover in combination with water-vegetation edge density (Akaike weight = 0.88). Breeding density was unrelated to water depth, contrary to a previous study at the site after a dyke breach significantly lowered water levels, suggesting that above a certain depth threshold other habitat preferences take precedence. We recommend that management of created wetlands for Least Bitterns focus on maintaining stable water levels of at least 25 cm on average during the breeding season and manipulating them as required later on in order to promote hemi-marsh conditions. UAS can enhance wetland habitat research and monitoring by improving the precision and efficiency of data collection in the field while reducing disturbance compared to ground-based surveys.

Introduction

The Least Bittern (*Ixobrychus exilis*) is a secretive and, until recently, poorly studied marsh bird whose populations are threatened by loss and degradation of natural wetlands suitable for breeding (Winstead and King 2006; Poole et al. 2009; Rush et al. 2009). Least Bitterns tend to breed in wetlands dominated by tall, robust emergent vegetation, where they build nesting platforms and feed often in close proximity to open water (Bogner and Baldassarre 2002; Lor and Malecki 2006; Jobin et al. 2011a). Recent studies have identified water-vegetation edge (sometimes referred to as "interspersion") as an important factor in habitat selection (Rehm and Baldassarre 2007; Moore et al. 2009; Rush et al. 2009; Darrah and Krementz 2010; Bolenbaugh et al. 2011), which is likely related to the Least Bittern's habit of stalking along the edge of emergent vegetation or building foraging platforms at the water-vegetation interface and picking prey out of the water (Weller 1961; Poole et al. 2009). Areas with higher edge density may therefore provide greater foraging potential and support higher densities of breeding bitterns.

The Least Bittern has been listed as Threatened in Canada since 2003 under the federal Species at Risk Act (SARA 2002). Environment Canada (2014) has identified 115 sites among four provinces deemed to contain critical breeding habitat, including several wetland impoundments in Quebec that are amenable to management to promote use by Least Bitterns. The largest of these is a designated Migratory Bird Sanctuary in Baie-du-Febvre where upwards of 30 breeding pairs have previously been censused (Jobin et al. 2007, 2009). In order to guide the creation of a site management plan, we conducted a study of Least Bittern habitat relationships within the wetland with the aim of identifying which parameters are most strongly related to breeding density.

In an effort to overcome the challenges of assessing habitat cover from ground level, in particular fine-scale measurement of water-vegetation edge density in areas of tall and dense vegetation, we made use of a small unmanned aircraft system (UAS) capable of gathering timely aerial imagery at sub-decimeter spatial resolution. These devices have recently been shown to be advantageous for fine-scale surveying of rangelands and forests (e.g. Rango et al. 2009; Getzin et al. 2012), and a trial comparison of land cover estimates made from UAS aerial imagery of the

Baie-du-Febvre wetland to estimates made on the ground demonstrated that the data were reliable (Chabot and Bird 2013).

Methods

Study site

The 128-ha wetland impoundment (Fig. 1) is situated on restricted Department of National Defence property in Baie-du-Febvre, Quebec, on the south shore of the St. Lawrence River (46˚09', 72˚44'). Managed by Ducks Unlimited Canada, the impoundment was built on former agricultural and forested land and flooded in 1988. It is partitioned into three basins separated by dykes: a large south basin and two smaller north-east and north-west basins, with canals running around the site's periphery and along one side of each transecting dyke. The site has grown into an emergent herbaceous wetland dominated early in the summer season by cattail (*Typha latifolia* and *T. angustifolia*, with dead stands left over from the previous year) as well as bur-reed (*Sparganium eurycarpum* and *S. emersum*) as the season progresses. Smaller amounts of flowering rush (*Butomus umbellatus*), sedges (*Carex stricta* and *C. comosa*), wild rice (*Zizania aquatica*), buttonbush (*Cephalanthus occidentalis*) and arrowhead (*Sagittaria latifolia* and *S. rigida*) also occur. Invasive reed canary grass (*Phalaris arundinacea*) grows along the dykes and outer margins of the wetland, and numerous species of floating vegetation occur in areas of standing water.

Ground-based data collection

We surveyed Least Bitterns in 2011 in accordance with the call-broadcast protocol outlined by Jobin et al. (2011b) at 30 points previously established throughout the wetland during research conducted from 2004–2006 (Jobin et al. 2007; Fig. 1). Points were restricted to areas containing vegetation in which bitterns are known to nest, chiefly cattail and bur-reed. To maximize probability of detection, surveys were repeated four times over the course of the breeding season, on May 25–27, June 2–4, June 16–17 and June 27–28, from 4:47–11:43 a.m. The distance of detected bitterns from survey points was estimated, and for the purpose of the habitat analysis we only considered detections within 50 m. We used the number of vocalizing males detected as an approximation of the number of breeding pairs and quantified breeding density as the maximum number of vocalizing males detected at each point during a single survey (Jobin et al. 2009).

Average live and dead vegetation height within a 50-m radius was visually estimated at each point during the final bittern survey in late June. A botanical survey was carried out around each survey point from September 7–21 (Gilbert 2011), during which water depth was measured at the center as well as at 12.5 m and 25 m in each cardinal direction (nine measurements total, for points situated in the interior of the wetland) or along three equiangular transects on one side of the center (seven measurements total, for points along the outer margins and transecting dykes). For the analysis, we used the averages of all depth measurements made around each survey point. We opted to use the dispersed depth measurements made in September rather than single measurements made at the center of each survey point during the bittern surveys because we judged that the former were likely to provide estimates that were more representative of the whole areas within which we counted bitterns. Preliminary comparison of measurements taken at the center of each survey point in September to those taken during the final bittern survey in late June indicated that there was an overall 31.5% rise in water levels over the course of the summer but that the increase was uniform among survey points, as evidenced by a strong correlation between values from the two time periods ($r = 0.704$, $p < 0.001$).

Aerial data collection

We conducted an aerial survey of the wetland on July 27 from 10:15 a.m. – 2:20 p.m. using the AI-Multi UAS (Aerial Insight, Brandon, MB, Canada), a 2.1-m wingspan, 4-kg hand-launched electric airplane equipped with a camera and a miniature autopilot system (MP2028g by MicroPilot, Stony Mountain, MB, Canada) that executes preprogrammed flights fully autonomously from takeoff through to landing (for more detail, see Chabot and Bird 2013). The UAS components were transported by car to an agricultural field adjacent to the wetland and the system was assembled on site. The aircraft was programmed to cover the site in two successive flights at an altitude of 274 m (900 ft) and airspeed of ~60 km/h, each consisting of a series of back-and-forth transects during which the gimbaled downward-pointing camera (10-megapixel Canon S90) captured a sequence of overlapping photos with a spatial resolution of 8.8 cm/pixel.

The resulting 220 photos were stitched together into a seamless georeferenced image of the entire wetland (Fig. 1) by Pix4D (Lausanne, Switzerland) using an automated process that derives positional data for each photo from the autopilot's flight log. We then loaded the image into ArcMap v.10.1 (Esri ArcGIS, Redlands, CA, USA) and used the Spatial Analyst extension to classify land cover in a 50-m radius circular plot (7854 m^2) centered on each survey point using a supervised pixel-based spectral classification process described in detail by Chabot and Bird (2013). Briefly, samples of various cover classes (e.g. water, floating vegetation, cattail, bur-reed, etc.) were first manually identified with the aid of ground-truth data collected around each survey point during the botanical survey of September 7–21, a coarse-scale sketch of vegetation layout in the wetland produced following an aerial survey in 2006 (Jobin et al. 2007), and consultation with biologists familiar with the site. Based on these training samples, the full area of each plot was then automatically classified into the predefined set of classes. We ultimately narrowed classes down to "water" (including floating vegetation), "cattail" and "other emergent vegetation". Finally, we used FRAGSTATS (McGarigal and Marks 1995) to compute percent cover by class as well as water-vegetation edge length in each plot.

Statistical analyses

Results were analyzed using SPSS Statistics v.21.0 (IBM Corp., Armonk, NY, USA). We calculated descriptive statistics for all variables and assessed their distributions with Kolmogorov-Smirnov (K-S), Kurtosis and Skewness tests, and produced a Spearman's rank correlation matrix to check for multicollinearity among explanatory variables. We then used a model-selection approach based on Akaike's information criterion for finite sample sizes (AICc; Burnham and Anderson 2002; Burnham et al. 2011) to compare candidate regression models with number of vocalizing males detected as the dependent variable and the various habitat parameters as explanatory variables: percent cattail cover (%cattail), percent other emergent vegetation cover (%other), percent water cover (%water), water-vegetation edge length (edge), live vegetation height (liveheight), dead vegetation height (deadheight), and water depth (waterdepth). Although the dependent variable by nature had a Poisson distribution (K-S: $Z = 0.401$, $p = 0.62$), it also passed the null hypothesis test for a normal distribution (K-S: $Z = 1.200$, $p = 0.10$), and normal-distribution models proved to have lower AICc values than Poisson-distribution models. We therefore proceeded with normal-distribution linear regression models.

We ran a null model (intercept only) to serve as a baseline, against which we ran a series of single- and two-variable models. Due to sample size limitation (n = 30), we did not test models with more than two variables, nor did we consider interactions between variables. We considered models to have a good fit if the 95% confidence interval (CI) of parameter estimates (β) did not cross zero for any of the explanatory variables, and rejected two-variable models if they did not have more support than each of their associated single-variable models.

Results

Among the 30 points surveyed in the wetland, two vocalizing males were detected within 50 m at seven points, one vocalizing male was detected at 13 points, and none was detected at 10 points (Fig. 1). Mean live vegetation height around all survey points estimated during the final bittern survey in June was 150 cm (SD = 48 cm, range = 55–220 cm), mean dead vegetation height was 75 cm (SD = 33 cm, range = 0–120 cm), and mean water depth measured during the botanical survey in September was 55 cm (SD = 23 cm, range = 15–112 cm). Mean water cover (including floating vegetation) in 50-m radius plots surrounding survey points, as measured in the aerial imagery, was 27.5% (SD = 14.9%, range = 2.1–69.3%), mean cattail cover was 35.1% (SD = 19.2%, range = 0–78.1%) and mean cover by other species of emergent vegetation was 37.3% (SD = 16.0%, range = 0.4–80.4%). Cattail was detected in all but three plots and was the dominant vegetation (>50% of total emergent vegetation cover) in 14 plots. Bur-reed and/or flowering rush, which were difficult to differentiate in the aerial imagery, were detected in all but four plots, although the botanical survey suggested the former to be much more prevalent. Wild rice was detected in six plots, sedges were detected in three plots, buttonbush was detected in two plots and small amounts of canary grass along the outer margins and transecting dykes of the wetland were detected in 15 plots. Mean water-vegetation edge length in 50-m radius plots was 2.52 km (SD = 1.25 km, range = 0.26–4.93 km).

Regression model results are summarized in Table 1, while the values of habitat variables that showed a relation to bittern breeding density (adjusted $R^2 > 0$) are contrasted among plots with zero, one and two vocalizing males in Fig. 2. Breeding density was clearly best predicted by the model %cattail + edge (AICc = 50.92, w = 0.88, adjusted R^2 = 0.55; β_{cattail} = 0.030, 95% CI =

0.021–0.040; β_{edge} = 0.350, 95% CI = 0.197–0.502), with only marginal relative support ($\sum w_i$ = 0.12) for the models %other + edge, %other, and %cattail + %water (Table 1). Several other models had more support than the null model (ΔAICc = 21.08) but negligible relative probabilities (w < 0.01), namely %cattail, deadheight + edge, deadheight, and liveheight (Table 1). Breeding density was only weakly related to edge alone (adjusted R^2 = 0.04), and unrelated (adjusted R^2 < 0) to waterdepth or %water (Table 1).

Discussion

The Baie-du-Febvre wetland impoundment contains large abundances of cattail and bur-reed, both known to be used by Least Bitterns for nesting (Kent 1951; Bogner and Baldassarre 2002; Jobin et al. 2011a), though breeding bitterns in our study appeared to favor cattail. Exact availability of bur-reed among survey plots could not be measured because the image classification process we used could not adequately distinguish bur-reed from flowering rush and occasionally other types of vegetation (Chabot and Bird 2013), although botanical surveys within a 25-m radius of survey points suggested that bur-reed accounted for ~75% of total non-cattail emergent vegetation (Gilbert 2011). Vocalizing males were not detected in any of the three plots devoid of cattail (Fig. 1, points 24, 25 and 26), two of which were dominated by bur-reed and the other by wild rice, nor in the only plot dominated by sedges (Fig. 1, point 12). In contrast, cattail was the dominant emergent vegetation and occupied >40% of the total area in all seven plots in which two vocalizing males were detected. Observed positive relationships between breeding density and the height of live and dead vegetation are likely a reflection of the fact that cattail is the tallest vegetation in the wetland and the only type to leave sizable emergent dead stands that persist from year to year. These are present upon initial arrival of bitterns in May, whereas bur-reed stands only begin to flourish over the course of June. It may therefore be that bitterns primarily select cattail because its earlier availability affords structural and functional benefits such as materials for construction of nests and foraging platforms as well as cover from predators.

In keeping with recent studies, we found a positive relationship between water-vegetation edge density and presence and abundance of breeding Least Bitterns. This is the first study to use sub-decimeter aerial imagery to precisely map the water-vegetation interface at such a fine scale;

edge density was previously estimated from the ground in 50-m radius plots (Darrah and Krementz 2010; Bolenbaugh et al. 2011), or from coarser-scale aerial imagery in 200-m radius plots (Rush et al. 2009) or over entire individual wetlands (Rehm and Baldassarre 2007; Moore et al. 2009). By surveying 30 plots, we were able to detect the influence of edge on bittern density within a single wetland. Our edge values may have been inflated as a result of measurements being made along square pixels, which would tend to exaggerate the length of diagonal edges and potentially be amplified by the high resolution of our imagery. However, this bias would have been consistent in all plots. We found that edge alone did not adequately predict breeding density, but rather the combination of edge with cattail cover (Table 1). For example, edge length was above average in both bur-reed-dominated plots devoid of cattail where no vocalizing males were detected. Conversely, four other plots where breeding bitterns were absent (Fig. 1, points 3, 7, 10 and 30) had above-average cattail cover but reduced edge lengths ranging from 0.26–1.36 km compared to the overall mean of 2.52 km. Altogether, our results suggest that bitterns are primarily attracted to cattail stands and subsequently home in on areas of high water-vegetation edge density to establish their nests. Such areas may provide them with more foraging opportunities and/or greater prey abundance (Voigts 1976; Kaminski and Prince 1981; Rehm and Baldassarre 2007).

We found no relationship between breeding density and water depth in survey plots, whereas Jobin et al. (2007, 2009) in a previous study documented a clear decline of the population as a result of a dyke breach that drastically reduced water levels (mean = 18 cm) in the impoundment. In the breeding season following the breach, they found significant positive bivariate correlations between the number of bitterns detected and water depth as well as water cover among 27 of the same points we surveyed in 2011 (Jobin et al. 2007). Harms and Dinsmore (2013) found water depth at survey points to be positively associated with Least Bittern occupancy among 309 wetlands in Iowa, Tozer et al. (2010) found average wetland water depth to be positively associated with bittern abundance among 15 wetlands in Ontario, and Timmermans et al. (2008) found a positive correlation between annual water level fluctuations in Lakes Erie, Huron and Michigan and population indices of Least Bitterns in coastal marshes. Moore et al. (2009), similar to us, found no overall difference in water depth between occupied and unoccupied created wetlands (n = 35) in Illinois. A synthesis of results from these studies suggests that although Least Bitterns may occasionally occupy areas with water as shallow as 5–10 cm, they are more typically found in areas with a minimum depth of 20–30 cm, above which modest variation may have little or no effect on their density. Following the dyke breach in the Baie-du-Febvre impoundment, simply finding areas with sufficient water levels and cover likely became the primary driver of habitat selection by breeding bitterns; when the impoundment is adequately flooded, other habitat relationships take precedence.

Management Implications

Created wetlands play an important role in maintaining Least Bittern populations in Canada (Environment Canada 2014), notably in Quebec as evidenced by their recurrent occupancy by some of the province's largest populations (Jobin et al. 2011a, 2013). Increasing the availability and suitability of such habitats can help compensate for large-scale historical losses of the species' natural breeding wetlands (Horstman et al. 1998; Post 1998; Jobin et al. 2009; Moore et al. 2009), although managers must be mindful of the concurrent needs of other declining species as well as waterfowl. Based on our findings, we concur with previous studies in recommending that efforts to promote breeding Least Bittern use of created wetlands focus on ensuring adequate and stable water levels during the breeding season while maintaining a high degree of interspersion between water and robust emergent vegetation over the long term.

Promotion of "hemi-marsh" conditions is a common management recommendation for achieving high species diversity via an increase of food, visual isolation and spacing, water-vegetation interspersion and habitat diversity (Ma et al. 2010). Some degree of water level fluctuation is generally required to maintain these conditions as permanently stable levels will tend to lead to densification of emergent vegetation, which can hinder bird movements and foraging (Bancroft et al. 2002), while prolonged periods of low water levels can lead to the establishment of invasive species such as *Phragmites* and expose waterbirds to increased mammalian predation (Ma et al. 2010). Since water level fluctuations can disrupt nesting and brood-rearing, it is advisable to conduct hydrological manipulations outside of the breeding season (Kaminski et al. 2006; Jobin et al. 2009). The three-basin design of the Baie-du-Febvre impoundment lends itself to various management considerations, for example by maintaining the separate basins in different stages of plant succession, thereby increasing potential benefits for a high number of wetland species. Impoundment dykes should also be regularly inspected for weaknesses (e.g. muskrat tunnels, erosion) that could lead to breaches.

Unmanned Aircraft Assessment and Prospects

Burgeoning UAS technology, in particular compact platforms such as the one used in this study, are expected to increasingly contribute to environmental and ecological research and monitoring thanks to their ability to conveniently perform unobtrusive low-altitude aerial surveys yielding spatial data at an intermediate scale between conventional aerial imaging and ground-level data collection (Watts et al. 2012; Anderson and Gaston 2013). In habitats that are particularly challenging to survey on the ground, such as large and dense wetlands, UAS may even offer superior precision and accuracy. Upon comparing sketches of the Baie-du-Febvre wetland survey plots (25-m radius) made from the ground during the botanical survey using a combination of visual observations and line-intercept sampling (Gilbert 2011) to aerial imagery gathered by the UAS, Chabot and Bird (2013) noted that ground surveys tended to overestimate cattail cover and overlook small pools and channels of water. This was attributed to the fact that the typically tall and dense cattail tends to dominate the field of view at ground level and impede detection of small patches of other vegetation and water. Selecting a flight altitude for aerial image acquisition entails a trade-off between spatial resolution and area footprint. Factoring in required overlap between adjacent photos, a 274-m altitude allowed us to cover the 128-ha wetland in two flights (maximum battery endurance ~60 min) totaling 220 photos with a sufficient resolution to achieve our primary goal of fine-scale mapping of the water-vegetation interface. As a point of reference, we could readily detect 18-cm diameter orange plastic cones placed around the periphery of the wetland to validate image georeferencing.

Gathering land cover data with the UAS required one day in the field whereas ground-based surveys took five days. Moreover, data from the latter were restricted to a 25-m radius around survey points whereas the UAS gathered high-resolution data over the entire site, even though only 50-m radius circles around survey points were examined for this particular study. Having now determined that the most important variables affecting habitat quality for Least Bitterns (cattail and water-vegetation edge) can be measured with UAS data, a potential next step would be to create a habitat suitability index (HSI) for the entire wetland, making use of the full aerial image. UAS surveys could then be repeated and the HSI recalculated at prescribed time intervals as part of a long-term site monitoring program. Under this scenario, future ground-based surveys would only be required to check water levels, basal flooding of emergent vegetation, and dyke integrity. Furthermore, recent advancements in UAS-borne multispectral imaging, object-based image analysis and LiDAR promise to improve classification of different types of vegetation and enable remote measurement of vegetation height and density (Laliberte et al. 2011; Wallace et al. 2012). Also of significance, trial studies suggest that small electric UAS cause little to no disturbance to birds when flying as low as 30 m above the ground (Chabot and Bird 2012; Sarda-Palomera et al. 2012).

Advantages afforded in the field are partially offset however by the need to invest time in subsequent image processing and analysis, though new software solutions such as Pix4D that are specifically designed to automatically stitch and georeference UAS imagery using flight log data are much faster for processing large batches of photos than conventional image stitching software. For this study, we operated the UAS and performed image classification and analysis ourselves, which admittedly requires a specialized skill set and access to the proper software. New users of programmable fixed-wing UAS in particular face a steep learning curve, including the need for basic radio-control piloting skills in order to be able to override the autopilot if necessary. The AI-Multi UAS and accessories (including laptop-based ground control station, spare batteries, chargers, etc.) cost approximately US$20,000, though with proper use and maintenance it can complete several hundred flights at little additional cost, eventually requiring airframe replacement (~$2,000). Alternatively, as civil UAS applications continue to multiply, a service sector is likely to develop offering “on-demand” UAS data acquisition and processing, with several such services already operating (Watts et al. 2012). Organizations such as the Association for Unmanned Vehicle Systems International (www.auvsi.org) and UVS International (www.uvs-info.com) provide useful resources for prospective users, including directories of available platforms and services and up-to-date information on regulations governing the use of UAS.

Acknowledgements

We thank B. Jobin, L. Robillard, J. Tardif and S. Giguère for assistance with bittern surveys, H. Gilbert and A. Lachance for the botanical survey, G. Maillet for assistance with the UAS survey, G. Lewis for assistance with aerial image processing, and K. Panchuk and R. Gagnon for coordinating access to the study site. Funding and in-kind contributions were provided by the Kenneth M. Molson Foundation, Environment Canada (Interdepartmental Recovery Fund for Species at Risk), the Department of National Defence, the Canadian Wildlife Federation, Pix4D, Aerial Insight, MicroPilot and the Fonds Québécois de la Recherche sur la Nature et les Technologies.

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Table 1. Linear regression models of Least Bittern breeding density as a function of habitat parameters among 30 survey plots (50-m radius) in the Baie-du-Febvre wetland impoundment, Quebec, 2011.

Model[a]	ΔAICc[b]	w[c]	R^2 (adj)[d]
%cattail + edge	0	0.88	0.55
%other + edge	5.40	0.06	0.46
%other	6.30	0.04	0.42
%cattail + %water	7.72	0.02	0.42
%cattail	12.80	0.00	0.28
deadheight + edge	14.12	0.00	0.28
deadheight	14.75	0.00	0.23
liveheight	15.72	0.00	0.20
null	21.08	0.00	0
edge	21.14	0.00	0.04
waterdepth	23.56	0.00	-0.04
%water	23.56	0.00	-0.04

[a] All models include the intercept; %cattail = percent cattail cover (live and dead); %other = percent non-cattail emergent vegetation cover; %water = percent water cover, including floating vegetation; edge = water-vegetation edge length (km); deadheight = dead vegetation height (cm); liveheight = live vegetation height (cm); waterdepth = water depth (cm); null = null model (intercept only)
[b] Difference in Akaike's information criterion (for finite sample sizes) values between the model in question and the best explanatory model in the set = $AICc - AICc_{min}$; $AICc_{min} = 50.92$
[c] Relative probability that the model in question is the best explanatory model = $\exp(-\Delta AICc/2) / \sum(\exp(-\Delta AICc_i/2))$
[d] Adjusted coefficient of determination

Figure 1. The Baie-du-Febvre wetland impoundment, Quebec, shown in an aerial image constructed from 220 overlapping high-resolution photos taken by a small unmanned aircraft in July 2011, with numbered dots indicating locations of Least Bittern survey points and numbers in brackets indicating the number of vocalizing males detected within a 50-m radius.

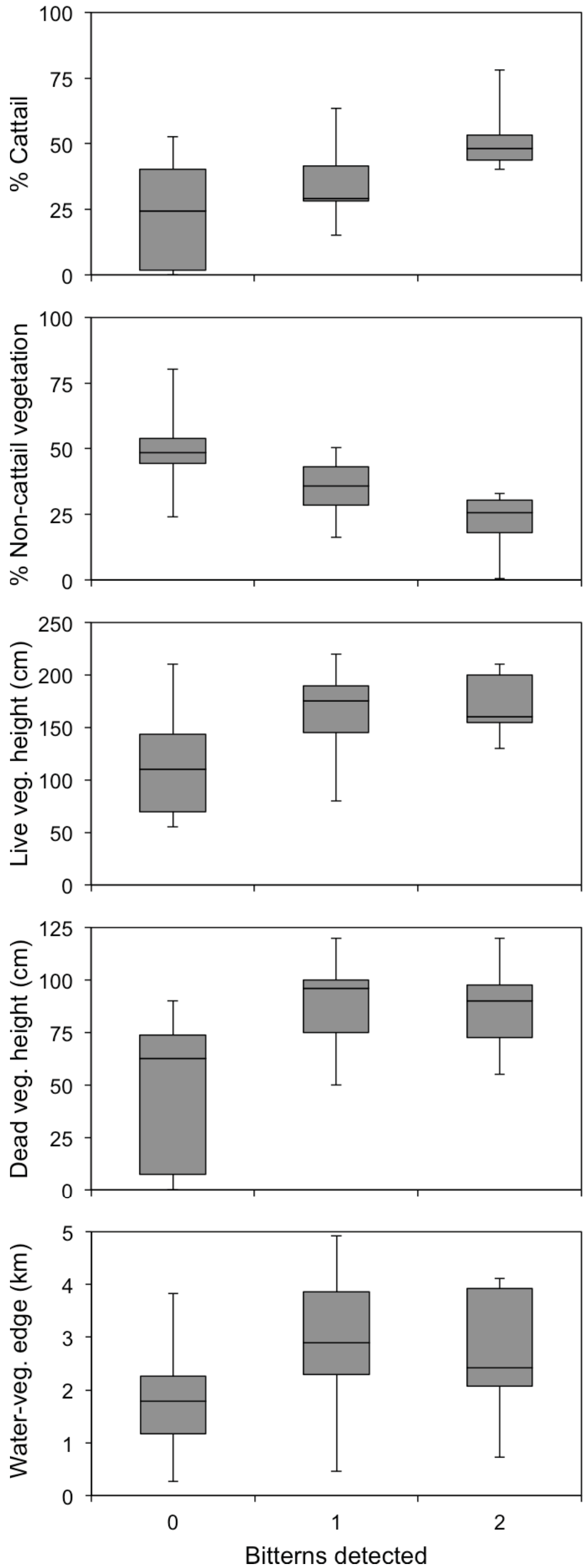

Figure 2. Box-and-whisker plots contrasting cattail cover, non-cattail vegetation cover, live and dead vegetation height, and water-vegetation edge length among 50-m-radius plots in which zero (n = 10), one (n = 13) and two (n = 7) vocalizing male Least Bitterns were detected in the Baie-du-Febvre wetland impoundment, Quebec, 2011.

CONNECTING STATEMENT

A UAS-based method of habitat data collection was validated and applied in the context of a case study of the least bittern, in which it proved beneficial for obtaining fine-scale data in a habitat that is challenging to navigate and assess at ground level. In the following chapter, the first of two in a case study of the common tern, the method is again applied in a study of habitat relationships in a large breeding colony, in this case with the additional benefit of minimizing disturbance of a highly sensitive species. This study will ultimately help inform any future efforts to conserve the common tern's vulnerable coastal habitat.

CHAPTER 4

HABITAT PARAMETERS AFFECTING NEST DENSITY, PLACEMENT AND TIMING IN A LARGE COASTAL COMMON TERN COLONY

Abstract

Nesting habitat relationships were studied in a large Common Tern (*Sterna hirundo*) colony (>6,000 pairs) on a barrier island complex in New Brunswick, with novel use of a small unmanned aircraft system (UAS) to map habitat. A model-selection approach based on Akaike's information criterion (AIC) was used to assess variables affecting nest density, placement and timing. Strong preference for nesting on washed-up Eelgrass (*Zostera marina*) stood out most across all aspects of nesting, with cumulative Akaike weights ($\sum w_i$) ranging from 0.46–1.00 among top models. Nest density (n = 45 plots) was also positively related to forb cover ($\sum w_i$ = 1.00), negatively related to grass cover ($\sum w_i$ = 0.91), and positively related to elevation ($\sum w_i$ = 0.85). Terns avoided placing their nests (n = 105) directly on sand substrate (observed: 3.8%; expected: 27.6%) and in dense grass habitat (observed: 3.8%; expected: 31.6%), and nested farther from the high tide line ($\sum w_i$ = 0.93) and near shorter vegetation ($\sum w_i$ = 0.63) than random control sites (n = 98). Earlier hatch date (n = 79) was best predicted by higher elevation ($\sum w_i$ = 1.00), with earlier nesters additionally tending to avoid open beach areas ($\sum w_i$ = 0.55), settle near taller vegetation ($\sum w_i$ = 0.34), and have less dead vegetation ($\sum w_i$ = 0.33) and more forbs ($\sum w_i$ = 0.16) in the immediate vicinity of their nests. The ecological significance of these findings is discussed. Use of UAS in colonial waterbird research and management is recommended following effective and low-disturbance application in this study.

Introduction

Ongoing global sea-level rise (Solomon *et al.* 2007) poses a threat to many coastal waterbird populations (Erwin *et al.* 2006, Brinker *et al.* 2007). Common Terns (*Sterna hirundo*), for example, have already incurred a 60% population decline (from 8,130 to 3,236 pairs) linked to island erosion in the Chesapeake Bay area, USA, from 1993 to 2003 (Erwin *et al.* 2011). Close to two thirds of North America's Common Tern population breeds along the Atlantic seaboard (Nisbet 2002), with upwards of 25% of the coastal population concentrated in just three localities: Great Gull Island, New York (upwards of 9,000 pairs); Monomoy National Wildlife Refuge, Massachusetts (upwards of 9,000 pairs); and Kouchibouguac National Park (KNP), New Brunswick (upwards of 7,000 pairs).

Terns in KNP breed on a coastal barrier sand island complex off the east coast of New Brunswick known as Tern Islands. Throughout population monitoring since the park's establishment in 1969, the number of pairs censused on Tern Islands has ranged from 1,419 in 1971 to 7,385 in 2008, with an average of ~6,000 pairs/year and no fewer than 3,300 pairs in a single year over the past three decades (E. Tremblay pers. commun.). The Tern Islands colony is the largest in Canada and may represent up to 9% of the entire Canadian Common Tern population according to the most recent estimates (Morris *et al.* 2012). However, the island complex has undergone significant geological alterations since 1930 (Dietz and Chiasson 2000), with a recent decrease in total area from 13.8 ha in 1984 (Young and Titman 1986) to 2.8 ha in 2005 (Craik and Titman 2009). In addition, the coasts of eastern New Brunswick are among the most vulnerable areas in Atlantic Canada to storm surge flooding and the coastal region of Kouchibouguac is projected to experience a relative sea-level rise of 1.00 ± 0.48 m from 2000–2100 (Forbes *et al.* 2006; Daigle 2012). These combined circumstances suggest that the future of the Tern Islands colony may be precarious and that management action may eventually be necessary in order to conserve it. Although the colony's abundance and productivity have been regularly monitored, there is a lack of data on habitat use, which would be valuable towards any conservation initiatives.

To address this gap, we studied habitat relationships of nesting terns on Tern Islands in 2012 with the specific objectives of identifying parameters that affect (1) nest density, (2) nest placement, (3) nest success and (4) nest timing. In an effort to overcome the challenges and minimize the disturbance associated with mapping habitat in a dense tern colony, we made use of a small unmanned aircraft system (UAS) capable of gathering aerial imagery at sub-decimetre resolutions. Such UAS have been successfully employed in recent years to conduct low-disturbance bird surveys (Chabot and Bird 2012; Sarda-Palomera *et al.* 2012) as well as collect high-resolution habitat imagery of rangelands, forests and wetlands (Laliberte *et al.* 2011; Getzin *et al.* 2012; Chabot and Bird 2013).

Methods

Study site

Tern Islands are currently composed of two main islands (hereby referred to as island 1, to the north, and island 2, to the south) ~300 m apart, ~800 m off the east coast of New Brunswick. The islands are flanked to the east by the South Kouchibouguac Dune (Fig. 1), which offers shielding from the strong waves of the open sea. Topography on the islands is low-lying (mostly <2 m ASL) and sand is mostly stabilized by Marram Grass (*Ammophila breviligulata*) and lesser amounts of Sea Lyme Grass (*Leymus mollis*) in lower-lying areas, as well as scattered Common Yarrow (*Achillea millefolium*) and Pigweed (*Chenopodium album*). Vast mats of dead vegetation covered parts of the islands in 2012 and strips of Eelgrass (*Zostera marina*) deposited by very high tides and storm surges were strewn parallel to the shore around the outer areas of the islands (Fig. 2).

Ground-based data collection

During the 2012 breeding season, we selected 105 nests and 105 control sites (50 each on island 1 and 55 each on island 2) by generating random points in preexisting GIS polygons of Tern Islands. We used a handheld Garmin GPS to locate the nest and control points on site, and for the former we proceeded to locate the nearest nest containing at least one egg. Nests and control sites were marked with small pink and orange stake flags, respectively, placed at least 50 cm away from nests.

Nests were marked on 15 June and checked every 1–3 days until it could be established whether they hatched or failed. Since it was common for chicks to disappear from the immediate vicinity of their nests in under three days after hatching, we decided to consider a pipping egg as evidence of nests having hatched. Where only pipping was observed, we assumed hatching occurred the following day (Nisbet 2002), otherwise we estimated hatch dates based on the appearance of hatchlings. We did not take into account the fate of chicks after hatching. It took until 9 July to determine the success of all nests, at which point four remaining nests with intact eggs that were suspected abandoned were watched for 10 min from a crouched-down position at least 10–15 m away while mobbing terns settled down to confirm that the nests were no longer being attended.

We recorded habitat parameters at each nest and control site from 25 June to 4 July. The immediate substrate was categorized as sand, dead terrestrial vegetation or dead eelgrass (*Zostera marina*). Given the frequent difficulty of ascertaining whether nest materials were added by the terns (Palmer 1941) or whether they were already in place and formed into a nest (e.g. clumps of eelgrass on top of sand), we defined substrate as the main material upon which eggs were directly deposited. Where applicable, we recorded the height of the substrate above sand/ground. We measured the distance to the nearest object (from the center of the bowl for nests) that could be used for cover (mainly live vegetation, occasionally driftwood or clumps of dead vegetation) as well as its height. We measured the distance to the nearest conspecific nest and counted the number of nests within a 2.5-m radius during peak nesting. To assess ground cover in the immediate vicinity of each site, we centered a 1.25-m hoop (2.5-cm diameter PVC piping) on each site, and with the aid of a step-stool extended a digital camera directly overhead and took a photo capturing the area within the hoop (~2.3 m above ground). The photos were cropped down to the hoop area on computer and ground cover was estimated by fitting the images under a 6 x 6 square grid created in PowerPoint v.14.3 (Microsoft Corp., Redmond, Washington, USA). The four corner cells not covering the hoop area were disregarded and the two side cells adjacent to each corner cell were counted as half-cells, for a total of 28 cells. In tallying ground cover, cells were entirely allocated to the most dominant cover class when it was estimated to occupy more than two thirds of the cell, otherwise they were split half-and-half between the two most dominant classes. Ground cover was categorized into sand, dead terrestrial vegetation, Eelgrass, live grass and live forbs.

In addition to nests and control sites, we established 45 plots (20 on island 1 and 25 on island 2) at random locations in order to examine nest densities in relation to habitat parameters. Each plot was marked with a wooden stake and the number of nests within a 5-m radius was counted on 17, 21 and 25 June. The maximum number of nests in each plot among the three surveys was retained for analysis. We recorded the location of each plot stake as well as each marked nest and control site using a high-accuracy Trimble Pathfinder backpack GPS unit. Throughout data collection, the device reported a positional error ranging from 10–60 cm.

Finally, on 21 June Parks Canada conducted a total nest count throughout the colony as part of its ongoing population monitoring program, which involved a dozen surveyors in a side-by-side line walking back-and-forth transects over the entire area of Tern Islands (Boyne and Hudson 2002).

Aerial data collection

We conducted an aerial survey of Tern Islands on 25 June 2012, from 07:05–07:40 using the AI-multi UAS (Aerial Insight, Brandon, Manitoba, Canada), a 2.1-m wingspan, 4-kg hand-launched electric airplane equipped with a miniature autopilot system (MP2028g by MicroPilot, Stony Mountain, Manitoba, Canada) that executes pre-programmed flights. We transported the components of the UAS by boat to the South Kouchibouguac Dune directly across from Tern Islands (Fig. 1) and assembled the system on site. We programmed the aircraft to repeatedly fly back and forth (northward-southward, 12 passes total, airspeed ~60 km/h) over the islands at an altitude of 91 m (300 ft) while an on-board downward-pointing Canon S90 10-megapixel camera shot a continuous series of overlapping photos with a spatial resolution of ~3 cm/pixel.

The photos were examined on computer and the clearest shots were selected to build a mosaic of the entire islands. The photos were stitched together using PTGui v.9.1 (New House Internet Services BV, Rotterdam, Netherlands) by first manually identifying a series of matching points in pairs of photos and then allowing the program to automatically perform fine-scale alignment and seamless blending of the images. In this manner a unified image of island 1 was created from five individual photos while an image of island 2 was created from eight photos. The images were then loaded into ArcMap v.10.1 (Esri ArcGIS, Redlands, California, USA) and georeferenced by linking orange or yellow plastic cones placed atop the 45 stakes marking the ground plots to their respective coordinates recorded by the Trimble GPS unit. Upon applying a second-order polynomial transformation to the images to improve the alignment of the cones with their specified coordinates, the root-mean-square error (RMSE; average distance between center of cones and coordinates) was 33 cm for island 1 (range = 11–58 cm) and 38 cm for island 2 (range = 7–81 cm).

Thanks to the high positional accuracy and spatial resolution of the imagery, it was possible to pinpoint the location of each marked nest and control site. For almost all of the former, a tern could be seen sitting on the nest, while for the latter it was often possible to discern the orange flags used to mark the sites. The overhead photos of each site taken on the ground additionally aided in pinpointing their locations. The islands were cropped along the wrack line representing the high tide line and seven control sites (three on Island 1 and four on Island 2) that ended up below the line were discarded from the dataset as they were deemed not to represent "available" habitat for tern nesting.

Habitat on the islands was then classified using the Spatial Analyst extension for ArcGIS (method described in detail by Chabot and Bird 2013). First, a series of polygons were manually drawn as representative "training samples" to create spectral signatures for various habitat classes. Identification was aided by the overhead photos of nests and control sites taken on the ground as well as photos of the ground plots. The Maximum Likelihood Classification function was then used to automatically classify the entire area of the islands into the following categories (Fig. 2): sand, grass, forb, pale dead vegetation (mainly dead grass) and dark dead vegetation (mainly Eelgrass but also some dead forbs). For analysis, we noted the habitat class at each nest and control point and extracted 2.5-m-radius circles centered on each point as well as 5-m-radius circles centered on each ground plot stake. Percent cover by each class was calculated in each circle using FRAGSTATS (McGarigal and Marks 1995) via the Patch Analyst v.5.1 extension (Ontario Ministry of Natural Resources, Thunder Bay, Ontario, Canada) for ArcGIS. In addition, we used the aerial imagery to measure the distance from each nest, control site and ground plot stake to the high tide line.

Finally, we used a digital elevation model (DEM) generated from an aerial LiDAR survey by the Nova Scotia Community College's Applied Geomatics Research Group flown on 17 July 2011, to note the elevation of each nest, control site and ground plot. The DEM had a horizontal spatial resolution of 1 m and elevation values were relative to mean sea level based on the Canadian Geodetic Vertical Datum of 1928. For ground plots, we noted the mean elevation within the 5-m-radius area. Where applicable, we added the substrate height recorded on the ground to the elevation value for nests and control sites.

Statistical analyses

We used SPSS Statistics v.21.0 (IBM Corp., Armonk, New York, USA) to analyze habitat parameters between nests and control sites, between hatched and failed nests, in relation to hatch date, and in relation to nest densities in ground plots. We calculated descriptive statistics for all variables and assessed the distributions of continuous variables with Kolmogorov-Smirnov, Kurtosis and Skewness tests. We checked for multicollinearity among continuous explanatory variables by producing Spearman's rank correlation matrices.

We then used a model-selection approach based on Akaike's information criterion for finite sample sizes (AIC_c) to build and assess generalized linear models incorporating explanatory habitat variables (Burnham and Anderson 2002; Burnham *et al.* 2011). We used binary logistic regression models to compare nests to control sites and hatched nests to failed nests, and linear regression models to analyze hatch date (inverse Gaussian distribution) and nest density (normal distribution). In all cases, we started by testing a null model (intercept only) followed by all single-variable models, noting their AIC_c values and parameter estimates (β) and ranking them by relative likelihood ($l_i = \exp((AIC_{c\ min} - AIC_{c\ i})/2)$). Models with a lower AIC_c value than the null model and in which the 95% confidence interval (CI) of β did not cross zero (in the case of categorical variables with more than two categories, at least one β value for which the 95% CI did not cross zero) were considered significant, and among them all those that were ≥5% as likely as the top model ($AIC_{c\ min}$) were "promoted" to form the bases for multiple regression models. Subsequent models were considered significant if they had a lower AIC_c value than their less-parameterized base model and the 95% CI did not cross zero for any of the parameter estimates, and again those that were ≥5% as likely as the top model were promoted. This process was repeated until models could no longer be improved. We did not include interactions in the models because none were *a priori* hypothesized and our aim was to achieve a broad idea of which habitat parameters and combinations thereof influence nest site selection, success and timing, as opposed to teasing out the best possible models. Where appropriate, we calculated the cumulative weight ($\sum w_i$) of individual variables among the final set of models by summing the l values of models that included a given variable and dividing by $\sum l_i$ of all models (Burnham and Anderson 2002).

Results

Descriptive statistics of continuous habitat variables for nests and control sites are presented in Tables 1 and 2 while substrate and habitat class frequencies are shown in Fig. 3. Based on the aerial images cropped at the high tide line, there was 10,485 m^2 and 19,594 m^2 of available habitat on islands 1 and 2, respectively. As per the classified aerial images (Fig. 2), island 1 was composed of 8.8% sand, 38.1% grass, 7.3% forbs, 36.1% pale dead vegetation and 9.7% dark dead vegetation, while island 2 was composed of 5.0% sand, 33.4% grass, 8.2% forbs, 39.3% pale dead vegetation and 14.1% dark dead vegetation. According to the DEM from 2011, mean elevation was 1.49 m on island 1 and 1.30 m on island 2. Control sites likely oversampled beach areas around the periphery of the islands, seemingly as a result of them having shrunk in relation to the GIS polygons (created in 2002) used to generate random points, although this bias was reduced with the elimination of sites that ended up below the high tide line. For the same reason, nest locations may also have been biased towards the periphery of the islands.

The total nest count performed by the park recorded 2,695 nests on island 1 (0.26 nests/m^2) and 3,634 nests on island 2 (0.19 nests/m^2). This difference in nest density between the islands was reflected in our results by greater mean distance to the nearest nest and fewer nests within 2.5 m for nests on island 2 compared to island 1 (Table 1). Also, the vast majority of forbs on island 2 were concentrated in a low-lying area (Fig. 3) of low nest density through which water tended to creep at high tide, leading to the observation of lower mean forb cover around nests on island 2 compared to island 1 (Table 2). Otherwise, habitat data for nests were generally similar between the islands.

Compared to the null model (AIC_c = 283.20), there was support for more eelgrass within 62.5 cm (AIC_c = 273.10), greater substrate height (AIC_c = 274.77), more nests within 2.5 m (AIC_c = 275.21), shorter cover height (AIC_c = 277.35), shorter distance to the nearest nest (AIC_c = 279.64), less grass within 62.5 cm (AIC_c = 280.01), less sand within 62.5 cm (AIC_c = 280.69), more pale dead vegetation within 2.5 m (AIC_c = 280.77), greater distance to the high tide line (AIC_c = 280.81) and less sand within 2.5 m (AIC_c = 280.93) for nests compared to control sites. However, substrate (AIC_c = 250.96) and habitat class (AIC_c = 251.55) at the immediate site were by far the single-variable models that best distinguished nests from control sites, as terns avoided sand substrate in favor of Eelgrass and avoided sand and grass habitats in favor of pale and dark dead vegetation (Fig. 3). The latter two models are shown in Table 3 in relation to subsequent top multiple regression models. The combination of substrate and habitat class formed by far the top two-variable model (AIC_c = 224.64), followed by substrate and cover height (AIC_c = 239.81). Predictive performance was further improved by adding distance to high tide line to substrate and cover class (AIC_c = 221.85) and finally adding cover height (AIC_c = 220.37).

Seventy-nine (75.2%) of the 105 monitored nests hatched at least one egg. Means for habitat parameters are contrasted between hatched and failed nests in Table 4, however the small sample size of failed nests restricted the statistical power of the dataset. Compared to the null model (AIC_c = 119.58), the only variable that definitively distinguished hatched nests from failed nests was the number of nests within 2.5 m, with failed nests having fewer on average (AIC_c = 115.52, β = 0.14, 95% CI = 0.02–0.25). Nevertheless, the results hinted that failed nests may have tended to be less elevated, closer to cover, farther from the nearest nest, or generally surrounded by less sand, less dead vegetation, more grass or more forbs than hatched nests (Table 4).

Mean hatch date was June 27 (range = June 19 – July 10). Hatch date was primarily related to elevation ($\sum w_i$ = 1.00), with more elevated nests tending to hatch earlier, but several other variables improved prediction of hatch date when added to elevation in multiple regression models (Table 5). These included: amount of sand within 2.5 m ($\sum w_i = 0.55$; positive relationship to Julian hatch date); amount of dark dead vegetation within 2.5 m ($\sum w_i = 0.46$; negative relationship); cover height ($\sum w_i = 0.34$; negative relationship); amount of dead terrestrial vegetation within 62.5 cm ($\sum w_i = 0.33$; positive relationship); habitat class ($\sum w_i = 0.18$; nests in dark dead vegetation habitat hatching earliest, followed by pale dead vegetation and finally sand); amount of forbs within 62.5 cm ($\sum w_i = 0.16$; negative relationship); distance to the high tide line ($\sum w_i = 0.05$; negative relationship); and amount of grass with 2.5 m ($\sum w_i = 0.02$; negative relationship).

The maximum number of nests in 5-m-radius ground plots ranged from 0–68 (mean = 17.4). As shown in Table 6, nest density was clearly best explained by a model incorporating amount of dark dead vegetation (positive relationship), amount of forbs (positive relationship), amount of grass (negative relationship) and elevation (positive relationship). However, there was also marginal support for nest densities tending to be higher in plots on island 1 ($\sum w_i = 0.12$) and in plots containing more pale dead vegetation ($\sum w_i = 0.09$).

Discussion

This is the first study of Common Tern nesting habitat to make use of an information-theoretic approach to rank candidate models, offering novel insight into the relative importance of various parameters in explaining nest density, placement and timing. Past studies have measured habitat parameters (chiefly cover) at various scales around nests. Our smallest scale of 62.5-cm radius, which we considered microhabitat, corresponds to roughly twice the total body length of a Common Tern. Our next scale of 2.5-m radius, considered macrohabitat, represents 16 times the microhabitat area and encompassed adequate variation among sites in conspecific nest density for statistical analyses. Nests within a 2.5-m radius could also be reliably counted by a single person. Our largest scale of 5-m radius, used for nest density analysis, could be reliably surveyed by two people.

Affinity for Eelgrass (i.e. dark dead vegetation) stood out more than any single other habitat parameter across all aspects of nesting. Nest density in 5-m radius plots was most strongly related to amount of dark dead vegetation (Table 6), nest substrate was highly skewed towards Eelgrass (Fig. 3a, Table 3), nest habitat was most skewed towards dark dead vegetation (Fig. 3b, Table 3), nests had a disproportionately high average amount of Eelgrass within 62.5 cm (Table 2), and earlier nesters were more frequently situated in dark dead vegetation habitat and tended to have more dark dead vegetation within 2.5 m (Table 5). Strong affinity for Eelgrass was observed by Burger and Lesser (1978), and several subsequent studies also reported Common Terns nesting on Eelgrass mats or wrack (Houde 1983, Burger and Gochfeld 1991, Rounds *et al.* 2004). Advantages of nesting on Eelgrass may include superior egg camouflage, nearby cover in the case of narrow mats strewn through live vegetation, and flood protection conferred by the thickness of mats (Burger and Lesser 1978). Nests in our study tended to have higher substrate height than control sites (Table 1), and substrate height was highly correlated with Eelgrass cover within 62.5 cm. Given the susceptibility of Tern Islands to very high tides, it seems likely that flood protection plays a role in preference for Eelgrass.

Also in keeping with previous studies, Common Terns on Tern Islands nested more frequently in relatively open areas than highly vegetated areas, but nevertheless tended to situate their nests at a certain proximity to some form of cover, usually live vegetation. This was evident in the observation that distance to cover showed much less overall variation among nests than control sites (Table 1). The preference for open areas was less pronounced at the 2.5-m radius scale than at the 62.5-cm radius scale, especially on island 1 where nests had more grass on average within 2.5 m than control sites (Table 2). We did not measure overhead visibility of nests as it was evident in the field and has previously been established that Common Terns rarely nest under overhanging vegetation (Gochfeld and Burger 1987, Burger and Gochfeld 1988, Ramos and del Nevo 1995). Only four of 105 nests were directly in grass habitat and a single nest was in forb habitat (Fig. 3b), and nest density was negatively related to amount of grass in 5-m radius plots (Table 6). We also found that vegetation near nests tended to be shorter than near control sites (Tables 1 and 3). Blokpoel *et al.* (1978) argued that overly tall or dense vegetation may hinder social stimulation and group action by reducing the visibility of conspecifics, provide insufficient landing or nest-building space, and/or reduce visibility of approaching predators.

These drawbacks would not be encountered in open areas, and by nesting near vegetation terns may still benefit from landmarks for nest recognition by adults and chicks as well as cover from weather and predators. However, several studies found higher predation rates on nests in open areas than in more vegetated areas (Lemmetyinen 1973, Burger and Lesser 1978, Storey 1987).

We found evidence of nest aggregation within the colony, indicated by shorter average distance to the nearest nest and greater nest density within 2.5 m for nests compared to control sites (Table 1). Coloniality by definition implies aggregation, and it is generally assumed that a significant advantage Common Terns derive from coloniality is communal defense against predators, as evidenced by their aggressive mobbing behavior (Burger and Gochfeld 1991). However, it is less clear whether patterns of aggregation within colonies are driven by predator protection or simply crowding of preferred habitats. Houde (1983) suggested that lower densities in grassier areas may simply be due to limited nest space, whereas high-density aggregations in more open areas may arise in part because reduced concealment from predators makes intense mobbing the most effective defense. If this were the case, we might expect earlier nesters to show some preference for more vegetated areas. We found only marginal evidence that they preferred sites with more grass within 2.5 m, though there was also modest evidence that they preferred nesting near taller vegetation (Table 5).

An interesting finding of this study was some evidence of preference for forbs. Although forbs were overall scarce on Tern Islands, earlier nesters tended to have more forbs within 62.5 cm (Table 5) and amount of forbs, when combined with dark dead vegetation, greatly improved prediction of nest density in 5-m radius plots (Table 6). Burger and Gochfeld (1990) conducted a laboratory experiment in which individually caged Common Tern chicks were reared with either Seaside Goldenrod (*Solidago sempervirens*), Beach Grass (*Ammophila breviligulata*) or both. Chicks reared with Goldenrod eventually moved directly under the vegetation, whereas those reared with Beach Grass merely moved closer to it but not under it. Those reared with both showed preference for Goldenrod. The authors speculated that the forb may offer superior cover since there is more room under the leaves, compared to grass which has more stems with less open space under them. To our knowledge, evidence of this preference of Common Terns for forbs over grass has not previously been found in the field.

Our finding that earlier nesters preferred more elevated sites (Table 5) was previously demonstrated by Nisbet *et al.* (1984). We also found that nest density tended to be higher in more elevated plots (Table 6), and greater average elevation may furthermore explain the overall higher nest density on island 1 than island 2. We identified several additional variables that improved prediction of hatch date when combined with elevation, including aforementioned dark dead vegetation, height of nearest cover, and forbs within 62.5 cm. Also of interest is the apparent avoidance of open beach habitat around the periphery of the islands by earlier nesters, as evidenced by less sand within 2.5 m and lower frequency of sand habitat among earlier nesters (Table 5). Possible explanations for this are reduced availability of cover and greater vulnerability of beach areas to flooding by waves as well as to avian predation. Average distance to cover among seven nests in the study with >30% sand within 2.5 m was 35.9 cm, compared to the overall average of 19.3 cm. Cover on the beach was also generally meager (e.g. a few blades of grass). Regarding predation, there have been reports of higher egg and chick losses to gulls among peripheral nests in tern colonies compared to more central nests (Becker 1995, Yorio and Quintana 1997). Nests on Tern Islands are commonly preyed upon by Herring Gulls (*Larus argentatus*), Great Black-backed Gulls (*L. marinus*), American Crows (*Corvus brachyrhynchos*), Common Ravens (*C. corax*), Northern Harriers (*Circus cyaneus*) and possibly owls, though there are no terrestrial predators (E. Tremblay pers. commun.). Greater distance to the high tide line among nests compared to control sites (Tables 1 and 3) as well as among earlier nesters (Table 5) may also be explained by flooding or predator avoidance.

We were unsuccessful at identifying habitat parameters that distinguished hatched nests from failed nests, beyond greater nest density around the former. As discussed above, this could either suggest that nests tended to fail due to predation facilitated by fewer neighboring conspecifics to form mobs, or simply because they were in poor quality habitats that tended to be avoided by conspecifics. At least four nests likely failed due to flooding. To minimize disturbance to the colony, we stopped monitoring nests after it was confirmed that at least one egg had hatched or was pipping, which resulted in a statistically limited sample of 26 failed nests. Measuring hatching success (proportion of hatched eggs/nest) may have yielded more insight into habitat parameters affecting nesting success.

In summary, we have gathered novel information on nesting habitat relationships in the third largest Common Tern colony on the Atlantic seaboard, and in doing so additionally provided some new insights into the species' general habitat preferences. Such information is valuable in the event that coastal colonies come under threat from erosion or rising sea level and habitat conservation efforts are required. As a final note, we wish to highlight our successful use of a small UAS for fine-scale mapping and subsequent digital classification and analysis of habitat on Tern Islands, a first to our knowledge in this field of research. The UAS could be conveniently deployed from a dune nearby the islands and repeatedly flown over the colony at low altitude without causing terns to flush off their nests, which was of great benefit for pinpointing nest locations. Although ground-based data collection in the colony collectively caused considerable disturbance, much additional disturbance was spared by using the UAS to collect macrohabitat data. We encourage colonial waterbird researchers and managers to consider taking advantage of this burgeoning technology. Watts *et al.* (2012) and Anderson and Gaston (2013) provide useful overviews of available UAS technology in the context of scientific research.

Acknowledgements

We thank G. Maillet for much assistance throughout data collection, E. Tremblay for logistical and administrative assistance, D. Saunders and L. Laltoo for GPS data collection and GIS assistance, M. Mahoney and D. Colville for supplying DEM data, R. Titman for general assistance with study design and preliminary work, and B. Martin, G. Daigle and D. MacDonald for facilitating field work. The UAS survey was authorized by Transport Canada in accordance with a Special Flight Operation Certificate (#12007), and the study was authorized by a Parks Canada Agency Research and Collection Permit (#KOU-2012-10913) as well as a McGill University Animal Use Protocol (#5394). Funds and in-kind contributions were provided by the Kenneth M. Molson Foundation, the New Brunswick Wildlife Trust Fund, the Canadian Wildlife Federation, Parks Canada, Aerial Insight, MicroPilot, and the Fonds Québécois de la Recherche sur la Nature et les Technologies.

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Table 1. Summary statistics of habitat parameters measured at Common Tern nests and random control sites on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

		Nests				Control sites			
Variable	Island	*n*	Mean ± SE	SD	Range	*n*	Mean ± SE	SD	Range
Substrate	1	50	1.9 ± 0.5	3.7	0–14	47	0.6 ± 0.3	1.8	0–7
height	2	55	3.2 ± 0.7	5.0	0–18	51	1.1 ± 0.5	3.9	0–24
(cm)*	1 + 2	105	2.6 ± 0.4	4.5	0–18	98	0.9 ± 0.3	3.1	0–24
Elevation	1	50	1.46 ± 0.05	0.33	0.99–2.74	47	1.45 ± 0.05	0.36	0.81–2.43
(m)	2	55	1.39 ± 0.05	0.37	0.74–2.11	51	1.35 ± 0.06	0.39	0.71–2.09
	1 + 2	105	1.42 ± 0.03	0.35	0.74–2.74	98	1.40 ± 0.04	0.37	0.71–2.43
Distance to	1	50	14.2 ± 1.4	9.6	1.3–31.4	47	10.8 ± 1.3	8.6	0.1–31.7
high tide	2	55	14.9 ± 1.5	11.3	2.3–39.3	51	12.6 ± 1.1	8.2	0.3–28.4
line (m)*	1 + 2	105	14.5 ± 1.0	10.5	1.3–39.3	98	11.7 ± 0.8	8.4	0.1–31.7
Distance to	1	50	17.7 ± 2.8	20.0	5–130	47	47.4 ± 16.3	112.0	0–483
nearest	2	55	20.6 ± 2.9	21.8	5–115	51	10.9 ± 3.4	24.3	0–139
cover (cm)	1 + 2	105	19.3 ± 2.0	20.9	5–130	98	28.4 ± 8.2	81.2	0–483
Nearest	1	50	31.3 ± 1.5	10.6	10–60	47	36.0 ± 2.2	15.2	10–69
cover height	2	55	30.5 ± 1.4	10.7	10–55	51	36.3 ± 2.3	16.4	10–66
(cm)*	1 + 2	105	30.9 ± 1.0	10.6	10–60	98	36.2 ± 1.6	15.8	10–69
Distance to	1	50	112.4 ± 7.7	54.4	48–348	47	129.6 ± 15.5	106.1	18–440
nearest nest	2	55	142.5 ± 11.6	86.3	48–474	51	208.4 ± 29.2	208.7	27–949
(cm)*	1 + 2	105	128.2 ± 7.2	74.1	48–474	98	170.6 ± 17.3	171.3	18–949
Nests within	1	50	8.4 ± 0.7	4.9	0–26	47	6.1 ± 0.7	4.6	0–19
2.5m*	2	55	5.5 ± 0.6	4.4	0–21	51	3.5 ± 0.5	3.9	0–20
	1 + 2	105	6.9 ± 0.5	4.8	0–26	98	4.8 ± 0.4	4.4	0–20

* Denotes a significant difference between nests and control sites (both islands combined) for the variable in question, as evidenced by a parameter estimate for which the 95% confidence interval did not cross zero in a single-variable binary logistic regression model.

Table 2. Summary statistics of ground cover at micro- (62.5-cm radius) and macro-habitat (2.5-m radius) scales around Common Tern nests and random control sites on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

		Nests				Control sites			
Variable	Island	*n*	Mean ± SE	SD	Range	*n*	Mean ± SE	SD	Range
% Sand (micro)*	1	50	11.0 ± 2.5	17.3	0–64.3	47	23.3 ± 5.6	38.3	0–100
	2	55	9.8 ± 3.1	23.2	0–91.1	51	14.3 ± 3.9	28.0	0–100
	1 + 2	105	10.4 ± 2.0	20.5	0–91.1	98	18.6 ± 3.4	33.5	0–100
% Grass (micro)*	1	50	19.1 ± 2.3	16.0	0–57.1	47	24.5 ± 3.1	21.4	0–83.9
	2	55	21.6 ± 2.2	16.4	0–64.3	51	28.5 ± 3.1	22.2	0–76.8
	1 + 2	105	20.4 ± 1.6	16.2	0–64.3	98	26.6 ± 2.2	21.8	0–83.9
% Forb (micro)	1	50	11.3 ± 2.7	19.3	0–71.4	47	9.3 ± 3.0	20.9	0–89.3
	2	55	4.2 ± 2.5	18.8	0–100	51	5.2 ± 2.5	18.1	0–89.3
	1 + 2	105	7.6 ± 1.9	19.3	0–100	98	7.2 ± 2.0	19.5	0–89.3
% Dead terrestrial veg. (micro)	1	50	44.4 ± 3.0	21.5	7.1–92.9	47	38.9 ± 4.2	28.7	0–91.1
	2	55	51.3 ± 3.7	27.5	0–100	51	45.6 ± 4.1	29.3	0–100
	1 + 2	105	48.0 ± 2.4	24.9	0–100	98	42.4 ± 2.9	29.1	0–100
% Eelgrass (micro)*	1	50	14.2 ± 3.1	22.0	0–69.6	47	3.9 ± 1.3	9.2	0–46.4
	2	55	13.1 ± 2.6	19.6	0–66.1	51	6.4 ± 2.1	15.1	0–62.5
	1 + 2	105	13.6 ± 2.0	20.7	0–69.6	98	5.2 ± 1.3	12.6	0–62.5
% Sand (macro)*	1	50	5.2 ± 1.4	10.0	0–45.6	47	16.8 ± 4.5	30.8	0–98.8
	2	55	6.5 ± 2.1	15.2	0–66.4	51	7.1 ± 2.7	19.3	0–99.2
	1 + 2	105	5.9 ± 1.3	13.0	0–66.4	98	11.7 ± 2.6	25.8	0–99.2
% Grass (macro)	1	50	37.4 ± 3.6	25.5	0.2–90.2	47	34.8 ± 4.1	28.4	0–95.1
	2	55	29.1 ± 3.5	26.1	0–91.5	51	43.2 ± 5.0	35.5	0–97.2
	1 + 2	105	33.1 ± 2.5	26.0	0–91.5	98	39.2 ± 3.3	32.4	0–97.2
% Forb (macro)	1	50	9.0 ± 2.4	17.3	0–72.4	47	6.2 ± 2.6	17.8	0–89.0
	2	55	4.5 ± 1.9	14.2	0–97.9	51	6.8 ± 2.6	18.5	0–92.9
	1 + 2	105	6.6 ± 1.5	15.8	0–97.9	98	6.5 ± 1.8	18.1	0–92.9
% Pale dead vegetation (macro)*	1	50	37.0 ± 3.6	25.2	3.9–93.9	47	32.8 ± 3.3	22.8	0.7–86.4
	2	55	44.0 ± 3.7	27.2	0.1–94.9	51	32.4 ± 4.4	31.7	0.4–99.5
	1 + 2	105	40.7 ± 2.6	26.3	0.1–94.9	98	32.6 ± 2.8	27.7	0.4–99.5
% Dark dead veg. (macro)	1	50	11.5 ± 2.1	15.0	0–66.9	47	9.3 ± 1.8	12.2	0–66.1
	2	55	15.8 ± 2.0	14.7	0.4–66.9	51	10.5 ± 1.9	13.9	0.1–60.3
	1 + 2	105	13.8 ± 1.5	14.9	0–66.9	98	9.9 ± 1.3	13.0	0–66.1

* Denotes a significant difference between nests and control sites (both islands combined) for the variable in question, as evidenced by a parameter estimate for which the 95% confidence interval did not cross zero in a single-variable binary logistic regression model.

Table 3. Top single- and multi-variable logistic regression habitat models distinguishing Common Tern nests (n = 105) from random control sites (n = 98) on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

Model[a]	ΔAIC_c[b]	l[c]	Parameter estimates (± 95% CI)
sub + hab + dhtl + covh	0	1.00	$-4.57(\pm2.26)sub_s$ $-1.97(\pm1.35)sub_{dtv}$ $+1.74(\pm2.53)hab_s$ $-1.74(\pm1.53)hab_g$ $-1.54(\pm2.59)hab_f$ $+0.55(\pm1.19)hab_{pdv}$ $+0.05(\pm0.05)dthl$ $-0.03(\pm0.03)covh$
sub + hab + dhtl	1.48	0.48	$-4.52(\pm2.26)sub_s$ $-1.89(\pm1.33)sub_{dv}$ $+2.07(\pm2.52)hab_s$ $-2.14(\pm1.48)hab_g$ $-1.05(\pm2.53)hab_f$ $+0.56(\pm1.18)hab_{pdv}$ $+0.05(\pm0.04)dthl$
sub + hab	4.27	0.12	$-4.45(\pm2.26)sub_s$ $-1.30(\pm1.17)sub_{dv}$ $+1.82(\pm2.50)hab_s$ $-2.17(\pm1.46)hab_g$ $-1.55(\pm2.46)hab_f$ $+0.49(\pm1.14)hab_{pdv}$
sub	30.59	0.00	$-3.36(\pm1.30)sub_s$ $-1.39(\pm0.84)sub_{dv}$
hab	31.18	0.00	$-1.54(\pm1.27)hab_s$ $-2.90(\pm1.24)hab_g$ $-2.23(\pm2.29)hab_f$ $-0.36(\pm0.78)hab_{pdv}$
null	62.83	0.00	

[a] sub = substrate (s = sand, dtv = dead terrestrial vegetation, reference category = Eelgrass); hab = habitat class (s = sand, g = grass, f = forb, pdv = pale dead vegetation, reference category = dark dead vegetation); dhtl = distance to high tide line (m); covh = height of nearest cover (cm); null = null model (intercept only); all models include the intercept (parameter estimates not shown).
[b] Difference in Akaike's information criterion values between the model in question and the top explanatory model in the set = $AIC_{c\,i}$ - $AIC_{c\,min}$; $AIC_{c\,min}$ = 220.37.
[c] Relative likelihood that the model in question is as parsimonious as the top model in the set = $\exp(-\Delta AIC_c/2)$.

Table 4. Means (± SE) of habitat parameters measured at hatched (at least one egg) and failed Common Tern nests on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

Variable	Hatched nests (n = 79)	Failed nests (n = 26)
Substrate height (cm)	2.3 ± 0.5	3.5 ± 1.1
Elevation (m)	1.44 ± 0.04	1.38 ± 0.08
Distance to high tide line (m)	14.5 ± 1.2	14.5 ± 2.1
Distance to cover (cm)	20.2 ± 2.6	16.3 ± 1.9
Cover height (cm)	31.1 ± 1.1	30.2 ± 2.4
Distance to nearest nest (cm)	120.2 ± 6.8	152.3 ± 20.2
Nests within 2.5 m	7.5 ± 0.6	5.0 ± 0.7
% Sand within 62.5 cm	11.5 ± 2.3	7.2 ± 4.1
% Grass within 62.5 cm	19.6 ± 1.8	22.9 ± 3.5
% Forb within 62.5 cm	5.5 ± 1.5	13.9 ± 6.0
% Dead vegetation within 62.5 cm	49.8 ± 2.8	42.4 ± 5.0
% Eelgrass within 62.5 cm	13.6 ± 2.3	13.5 ± 4.4
% Sand within 2.5 m	6.5 ± 1.5	4.1 ± 2.5
% Grass within 2.5 m	30.5 ± 2.7	40.7 ± 5.8
% Forb within 2.5 m	5.1 ± 1.3	11.4 ± 4.7
% Pale dead vegetation within 2.5 m	43.4 ± 2.8	32.3 ± 5.6
% Dark dead vegetation within 2.5 m	14.4 ± 1.8	11.7 ± 2.3

Table 5. Top single- and multi-variable linear regression habitat models explaining Julian hatch date of Common Tern nests (n = 79) on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

Model[a]	ΔAIC_c[b]	l[c]	Parameter estimates (± 95% CI)
elev + s_{macro} + dtv_{micro}	0	1.00	-7.39(±3.15)elev +0.17(±0.09)s_{macro} +0.07(±0.05)dv_{micro}
elev + hab	1.22	0.54	-7.10(±3.06)elev +11.05(±5.98)hab_s +0.07(±4.94)hab_g +2.73(±2.40)hab_{pdv}
elev + ddv_{macro} + covh + f_{micro}	1.81	0.41	-8.68(±3.61)elev -0.13(±0.08)ddv_{macro} -0.15(±0.11)covh -0.11(±0.09)f_{micro}
elev + s_{macro} + ddv_{macro} + covh	1.87	0.39	-6.61(±3.59)elev +0.10(±0.08)s_{macro} -0.08(±0.07)ddv_{macro} -0.11(±0.11)covh
elev + s_{macro} + ddv_{macro}	3.28	0.19	-7.78(±3.45)elev +0.11(±0.08)s_{macro} -0.07(±0.07)ddv_{macro}
elev + ddv_{macro} + covh + dhtl	3.59	0.16	-6.88(±3.62)elev -0.11(±0.07)ddv_{macro} -0.14(±0.11)covh -0.11(±0.10)dhtl
elev + s_{macro}	4.72	0.09	-6.22(±3.15)elev +0.12(±0.09)s_{macro}
elev + ddv_{macro} + g_{macro}	5.34	0.07	-9.22(±3.44)elev -0.13(±0.08)ddv_{macro} -0.05(±0.05)g_{macro}
elev + ddv_{macro} + covh	5.46	0.07	-7.57(±3.64)elev -0.09(±0.08)ddv_{macro} -0.12(±0.12)covh
elev + ddv_{macro} + f_{micro}	5.73	0.06	-9.98(±3.58)elev -0.12(±0.08)ddv_{macro} -0.09(±0.09)f_{micro}
elev + ddv_{macro}	7.19	0.03	-8.84(±3.48)elev -0.09(±0.08)ddv_{macro}
elev	9.42	0.01	-7.15(±3.22)elev
null	23.86	0.00	

[a] elev = elevation (m ASL); s_{macro} = % sand within 2.5 m; ddv_{macro} = % dark dead vegetation within 2.5 m; g_{macro} = % grass within 2.5 m; dtv_{micro} = % dead terrestrial vegetation within 62.5 cm; f_{micro} = % forb within 62.5 cm; hab = habitat class (s = sand, g = grass, f = forb, pdv = pale dead vegetation, reference category = dark dead vegetation); covh = height of nearest cover (cm); dhtl = distance to high tide line (m); null = null model (intercept only); all models include the intercept (parameter estimates not shown).

[b] Difference in Akaike's information criterion values between the model in question and the top explanatory model in the set = $AIC_{c\,i}$ - $AIC_{c\,min}$; $AIC_{c\,min}$ = 477.15.

[c] Relative likelihood that the model in question is as parsimonious as the top model in the set = $\exp(-\Delta AIC_c/2)$.

Table 6. Top single- and multi-variable linear regression habitat models explaining Common Tern nest density in 5-m radius plots (n = 45) on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

Model[a]	ΔAIC_c[b]	l[c]	Parameter estimates (± 95% CI)
ddv + f + g + elev	0	1.00	+0.55(±0.15)ddv +0.63(±0.22)f -0.28(±0.10)g +15.49(±8.93)elev
ddv + f + pdv + isl	4.74	0.09	+0.65(±0.14)ddv +0.70(±0.24)f +0.18(±0.09)pdv +5.82(±4.51)isl_1
ddv + f + g + isl	5.92	0.05	+0.49(±0.16)ddv +0.56(±0.24)f -0.17(±0.09)g +4.93(±4.52)isl_1
ddv + f + g	7.61	0.02	+0.50(±0.17)ddv +0.62(±0.25)f -0.17(±0.09)g
ddv + f + pdv	8.06	0.02	+0.65(±0.15)ddv +0.76(±0.26)f +0.17(±0.09)pdv
ddv + f	16.62	0.00	+0.63(±0.17)ddv +0.64(±0.28)f
ddv	30.95	0.00	+0.64(±0.20)ddv
null	56.19	0.00	

[a] ddv = % dark dead vegetation; f = % forb; g = % grass; pdv = % pale dead vegetation; elev = mean elevation (m ASL); isl = island (1 or 2); null = null model (intercept only); all models include the intercept (parameter estimates not shown).
[b] Difference in Akaike's information criterion values between the model in question and the top explanatory model in the set = $AIC_{c\,i}$ - $AIC_{c\,min}$; $AIC_{c\,min}$ = 316.86.
[c] Relative likelihood that the model in question is as parsimonious as the top model in the set = exp(-ΔAIC_c/2).

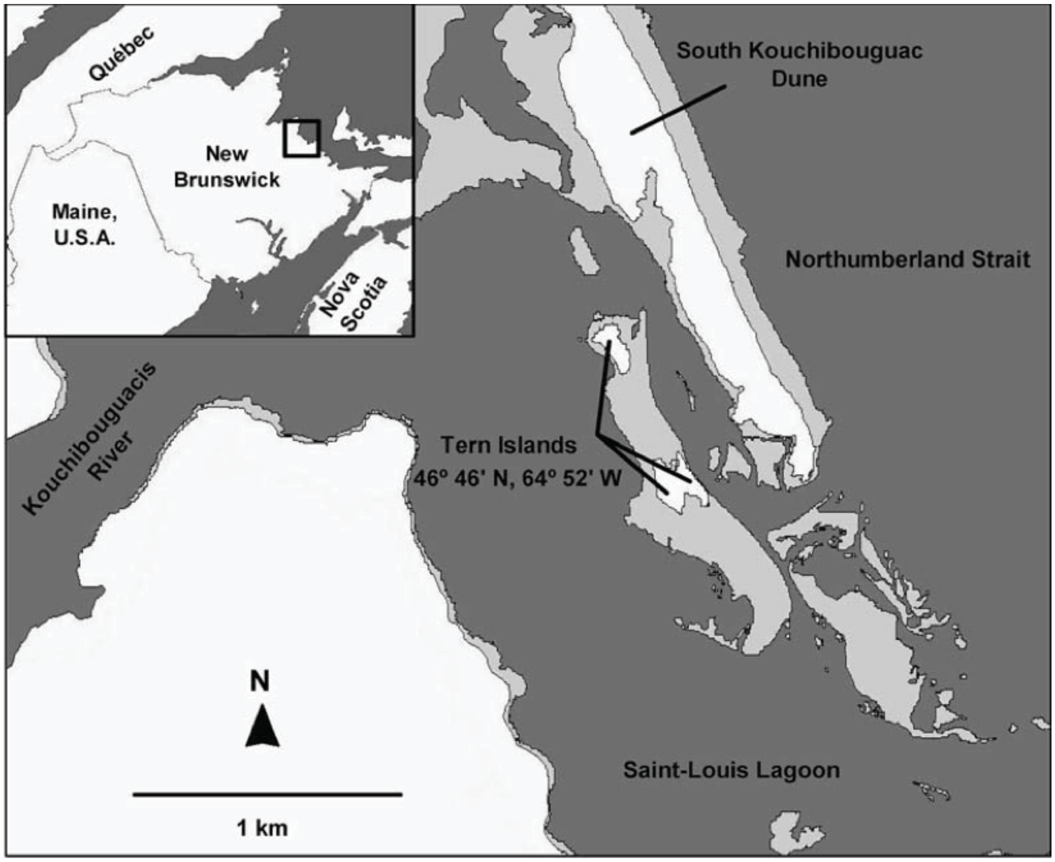

Figure 1. Map showing the location of Tern Islands, Kouchibouguac National Park, New Brunswick. Light grey areas represent intertidal zones (from Craik and Titman 2009).

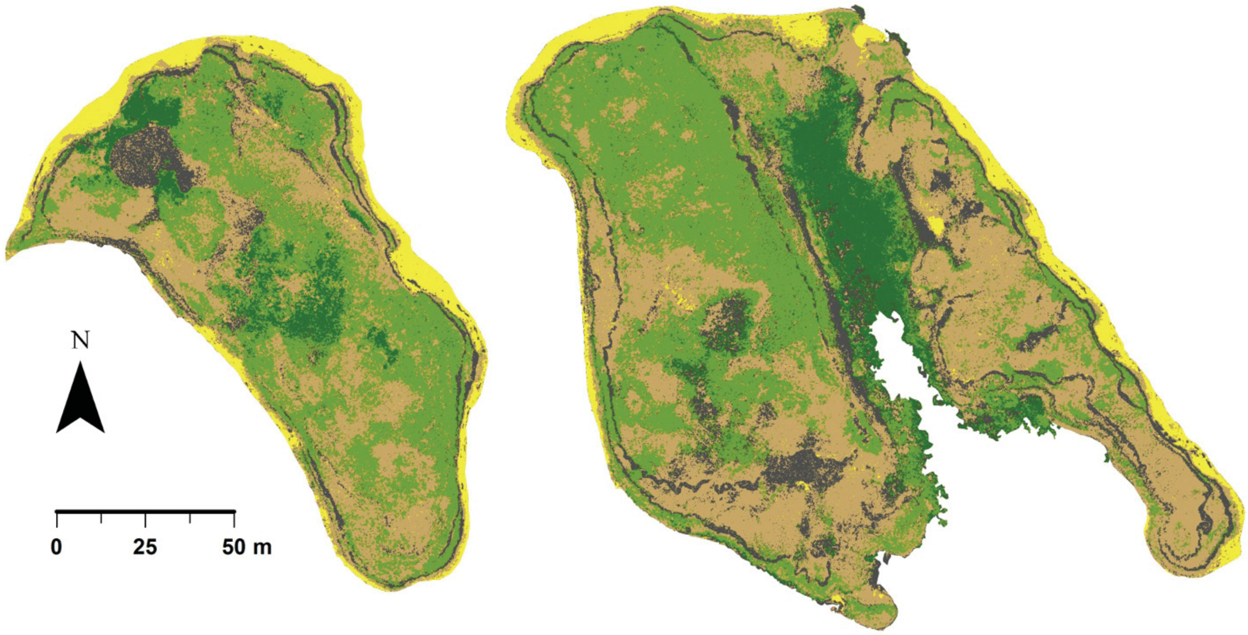

Figure 2. Classified aerial images of Tern Islands (left: island 1; right: island 2), Kouchibouguac National Park, New Brunswick, obtained from high-resolution photos taken by a small unmanned aircraft in June 2012. Light green areas represent grass, dark green areas represent forbs, beige areas represent pale dead vegetation (mainly beach grass), charcoal areas represent dark dead vegetation (mainly washed-up Eelgrass), and yellow areas represent sand.

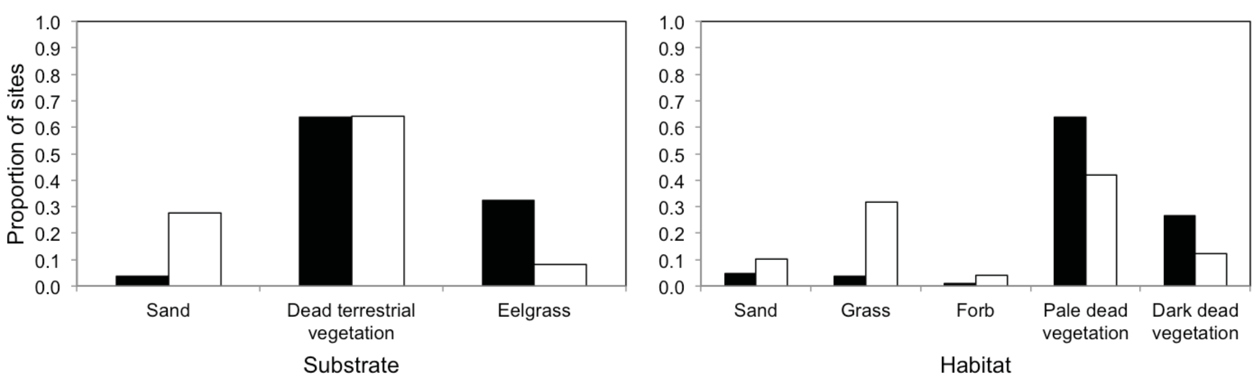

Figure 3. Proportional frequencies of substrate types and habitat classes among Common Tern nests (black bars; *n* = 105) and random control sites (white bars; *n* = 98) on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

CONNECTING STATEMENT

A second interest with regard to management of the common tern colony, as well as colonial waterbirds in general, is minimizing the disturbance caused by population monitoring. As alluded to in the previous chapter, a total colony nest count is carried out on the ground annually by a team of surveyors, which causes intense disturbance of the colony for several hours during the peak of the incubation period. The following chapter presents a rigorous method evaluation/validation of the small UAS as an unobtrusive means of conducting a colony population census. This capability could potentially be beneficial throughout the field of waterbird research and management.

CHAPTER 5

POPULATION CENSUS OF A LARGE COMMON TERN COLONY USING A SMALL UNMANNED AIRCRAFT

Abstract

Small unmanned aircraft systems (UAS) may be useful for conducting high-precision, low-disturbance waterbird surveys, but few data exist on their effectiveness at doing so. We evaluated the capacity of a small UAS to census a large (>6000 pairs) coastal Common tern (*Sterna hirundo*) colony of which ground surveys are particularly disruptive and time-consuming. We compared aerial photographic tern counts to ground nest counts in 45 plots (5-m radius) throughout the colony at three intervals over a nine-day period in order to identify sources of variation and establish a coefficient to estimate nest numbers from UAS surveys. We also compared a full colony ground count to full counts from two flights conducted the following day. Finally, we recorded colony disturbance levels over the course of 10 flights and 10 matched control periods. Linear regressions between aerial and ground counts in plots were very strong in all three comparison periods (R^2 = 0.972–0.989, $P < 0.001$) and regression coefficients ranged from 0.928–0.977. Full colony aerial counts were 93.6% and 94.0% of the ground count. Varying visibility of terns with ground cover, weather conditions and image quality, and changing nest attendance rates throughout incubation were likely sources of variation in aerial detection rates. Optimally timed UAS surveys of Common tern colonies following our method should yield population estimates in the 93–96% range of ground counts. Although the terns were initially disturbed by the UAS flying overhead, they rapidly habituated to it. Overall, we found no evidence of sustained disturbance to the colony by the UAS. We encourage waterbird researchers and managers to consider taking advantage of this burgeoning technology.

Introduction

Great effort and resources are invested worldwide in monitoring waterbird populations, which have long had important symbolic and functional value, historically in the context of recreational hunting and more recently as indicators of ecosystem health (Parnell et al. 1988, Kushlan 1993, Kingsford 1999, Diamond and Devlin 2003). Monitoring relies heavily on aerial surveys, which are convenient in aquatic environments and can rapidly cover large areas (Bechet et al. 2004, Kingsford and Porter 2009). However, ground surveys are also routinely carried out for smaller or more cryptic species, or to gather more precise data over relatively small areas. In addition to the time and effort required in the field, investigator disturbance is a well-documented drawback of ground-based monitoring (Rodway et al. 1996, Carney and Sydeman 1999, Blackmer et al. 2004, Carey 2009, Vertigan et al. 2012), although colonial waterbirds can habituate to some degree to regular research disturbance (Nisbet 2000).

In recent years, there has been increasing interest in the use of small unmanned aircraft systems (UAS) for surveying birds (Abd-Elrahman et al. 2005, Jones et al. 2006, Watts et al. 2010, Chabot and Bird 2012, Sarda-Palomera et al. 2012). The perceived promise of UAS is that they can approach the precision of ground surveys thanks to their low-altitude, high-resolution (<10 cm/pixel) aerial imaging capabilities while avoiding the disturbance associated with ground surveys thanks to their small size (<3-m wingspan) and quiet electric motors. Moreover, they can be deployed in a timely fashion over small (<3-km radius) aquatic environments that might otherwise be challenging to access or navigate at ground level. Whereas conventional aerial surveys of waterbirds have been the subject of numerous accuracy studies (e.g. Frederick et al. 1996, Boyd 2000, Cordts et al. 2002, Rodgers et al. 2005, Laursen et al. 2008), only two studies to date have presented quantitative data for entire flocks or colonies obtained using UAS and compared them to ground counts (Chabot and Bird 2012, Sarda-Palomera et al. 2012), and in both cases sample sizes were small. Therefore, there is a need to further assess the ability of UAS to achieve their perceived potential in order for the broader research and management community to give serious consideration to this emerging technology.

We evaluated a small "off-the-shelf" UAS for the purpose of conducting a population census of the third largest Common tern (*Sterna hirundo*) colony on the Atlantic coast (up to >7000 breeding pairs), situated on a barrier island complex in Kouchibouguac National Park (KNP), New Brunswick. Our objectives were to (1) rigorously compare aerial counts to ground counts over a multi-day period, (2) assess sources of variation and error in aerial/ground detection rates, (3) determine a reliable coefficient allowing estimation of the number of pairs in the colony based on the number of terns detected in the aerial imagery, and (4) assess how much disturbance, if any, the UAS causes to the colony.

Methods

Study site

The KNP Common tern colony is located on Tern Islands, a dynamic barrier sand island complex in the Saint-Louis Lagoon currently composed of two main islands (hereby referred to as island 1, to the north, and island 2, to the south) ~300 m apart, ~800 m off the east coast of New Brunswick, totaling ~3 ha in size (Fig. 1). Topography on the islands is low-lying (mostly <2 m ASL) and sand is mostly stabilized by Marram grass (*Ammophila breviligulata*) and lesser amounts of Sea lyme grass (*Leymus mollis*) in lower-lying areas, as well as scattered Common Yarrow (*Achillea millefolium*) and Pigweed (*Chenopodium album*). Vast mats of dead vegetation covered parts of the islands in 2012 and strips of Eelgrass (*Zostera marina*) deposited by very high tides and storm surges were strewn parallel to the shore around the outer areas of the islands. As the largest Common tern colony in Canada, Parks Canada has closely monitored its population over the past four decades by means of annual total nest counts performed on the ground (Dietz and Chiasson 2000).

Ground surveys

During the peak of the 2012 incubation period, we established 45 circular "comparison plots" of 5-m radius (20 on island 1 and 25 on island 2) by generating random points a minimum of 10 m apart in preexisting GIS polygons of Tern Islands. Collectively, the plots sampled a variety of habitats present on the islands (Fig. 2). We used a handheld Garmin GPS to locate the points on site and marked them with ~1-m wooden stakes. We placed an orange or yellow plastic cone atop each stake and subsequently recorded their locations using a high-accuracy Trimble Pathfinder backpack GPS unit (10–60-cm positional error reported throughout data collection).

We conducted total nest counts in each plot on 17, 21 and 25 June by extending a non-stretching string from the stake and positioning two surveyors at the 2.5-m and 5-m marks, respectively. The surveyors walked in a circle around the stake while keeping the string under tension, the former surveyor counting all nests between himself and the stake and the latter counting nests between himself and the first surveyor. Nests were counted if they contained at least one egg or at least one chick in or immediately next to them. On 21 June, Parks Canada conducted a total nest count throughout the colony as part of its ongoing population monitoring program, which involved a dozen surveyors placed side-by-side 2 m apart along a rope walking back-and-forth transects over the entire area of Tern Islands (Boyne and Hudson 2002).

Aerial surveys

From 16–25 June, we conducted aerial surveys of Tern Islands, weather permitting (no precipitation, winds <30 km/h), using the AI-multi UAS (Aerial Insight, Brandon, MB, Canada), a 2.1-m wingspan, 4-kg hand-launched electric airplane (Fig. 3) equipped with a miniature autopilot system (MP2028g by MicroPilot, Stony Mountain, MB, Canada) that executes preprogrammed flights. We performed a total of 12 flights (two on 16 June, one on 17 June, one on 18 June, three on 19 June, two on 22 June, and three on 25 June) lasting 25 min on average, all between 07:00 and 16:30. We transported the components of the UAS by boat to the South Kouchibouguac Dune directly across from Tern Islands (Fig. 1) and assembled the system on site. For each flight, the aircraft was programmed to fly repeated back-and-forth (northward-southward) transects over the islands at an airspeed of ~60 km/h, making six passes at an altitude of 91 m (300 ft) followed by six more at 122 m (400 ft) before returning to the dune and performing an autonomous belly-landing. While the aircraft was over the islands, an on-board downward-pointing Canon S90 10-megapixel camera housed in a gyro-stabilized mount and triggered by the autopilot shot a continuous series of overlapping photos with the lens fully zoomed out, the focus set to infinity, the shutter speed set to 1/1250 sec, and the aperture and ISO on an automatic setting that favored increasing the aperture opening as much as possible (*f*/2.0) before increasing the ISO sensitivity beyond 80. The spatial resolution of photos shot from 91 m was ~3 cm/pixel and those from 122 m was ~4 cm/pixel.

We examined the aerial photos on computer and selected the clearest 91-m shots from each flight on 17, 22 and 25 June to construct mosaics of the entire islands. Coverage of island 2 was incomplete in the 91-m imagery from 17 and 22 June, so we filled in the gaps with 122-m imagery. The photos were stitched together using PTGui v.9.1 (New House Internet Services BV, Rotterdam, Netherlands) by first manually identifying a series of matching points in pairs of photos and then allowing the program to automatically perform fine-scale alignment, rectification and seamless blending of the images. In this manner, unified images of island 1 were created from four to five individual photos and images of island 2 were created from seven to nine photos (Fig. 2). We then loaded the images into ArcMap v.10.1 (Esri ArcGIS, Redlands, CA, USA) and georeferenced them by linking the cones placed atop the 45 stakes marking the comparison plots to their respective coordinates recorded by the Trimble GPS unit. Upon applying second-order polynomial transformations to the images to improve the alignment of the cones with their specified coordinates, the root-mean-square error (average distance between center of cones and coordinates) ranged from 32–37 cm on island 1 and 29–55 cm on island 2.

We extracted 5-m radius circles centered on each cone (Fig. 4) from the aerial imagery in order to make comparisons with nest counts performed on the ground, retaining the clearest shot of each comparison plot among all flights performed on each day. For consistency, we excluded five plots from island 2 on 17 June and two plots on 22 June that were not covered by 91-m imagery. Using the count tool in Photoshop v.12.0 (Adobe Systems Inc., San Jose, CA, USA), we then counted the total number of terns visible in each plot in each of the three comparison periods (17 June, 21–22 June, and 25 June), with the underlying assumption that there should be at least one tern attending each nest almost all of the time (Burger and Gochfeld 1991). Whenever we observed two terns less than a body length apart, we considered that they were attending the same nest and only counted one. We then used the same approach to carry out total tern counts over the entire colony in the imagery from each of the two flights performed on 22 June (the day after the total nest count conducted by Parks Canada), in this case also counting terns in the portions filled in by 122-m imagery. We did not count terns located <1 m from the wrack line representing the high tide line as none were seen nesting this close to the water in the field and it was common for terns to loaf near the outer edge of the beach and in the shallow water around the periphery of the islands.

When counting terns in the aerial imagery, we suspected that ground cover influenced their detectability. In particular, they contrasted poorly with very pale dead vegetation (i.e. primarily dead grass). Using ArcGIS's Spatial Analyst extension (Esri, Redlands, CA, USA), we conducted supervised classification of ground cover (method described in detail by Chabot and Bird 2013) in imagery from 25 June (which was deemed to be of the highest quality) by first manually drawing a series of polygons serving as "training samples" to create spectral signatures for various cover classes (using photos taken on the ground to guide identification), then allowing the program to automatically classify the entire area of the islands into a predefined set of five classes: sand, grass, forb, pale dead vegetation, and dark dead vegetation (mostly eelgrass). We then used FRAGSTATS (McGarigal and Marks 1995) to calculate percent cover by class in each comparison plot.

Disturbance observations

In order to assess possible disturbance to the colony by the aircraft, we recorded disturbance levels on each island during 10 flights (we did not collect data during the first two flights on 16 June as these were considered practice runs) as well as 10 "matched" control periods of equal duration starting 10 minutes after each flight. An observer located on the South Kouchibouguac Dune (Fig. 1) with a clear view of both islands scored the overall disturbance level on each island at 30-second intervals from the moment the aircraft was launched until the moment it touched down, then did the same during control periods. Disturbance was scored as either "0" for no noticeable disturbance, "1" for moderate disturbance (localized flushing or visible agitation of terns affecting less than half of the island), or "2" for high disturbance (flushing of terns throughout most or all of the island, commonly known as an "upflight" or "panic"; Burger and Gocheld 1991, Nisbet 2002). In this manner, a total of 502 disturbance samples were recorded for each island throughout all flights and another 502 each throughout control periods (range = 47–55 samples/island/flight and control period). For each flight and control period, we summed the disturbance scores of all samples across both islands in order to obtain a single total colony disturbance score.

Statistical analyses

We performed statistical analyses with SPSS Statistics v.21.0 (IBM Corp., Armonk, NY, USA), using a significance level of 0.05. For all analyses, we first used Kolmogorov-Smirnov tests to confirm that variables were normally distributed. For comparison plots, we ran a linear regression analysis (Laursen et al. 2008) in each comparison period with ground counts as the independent variable and corresponding aerial counts as the dependent variable, and the intercept set to zero. We noted the regression coefficient (β) as well as its 95% confidence interval (95% CI), the significance level of the regression (F, P), and the model fit as expressed by the coefficient of determination (R^2). To test whether ground cover, specifically pale dead vegetation, influenced tern detectability, we ran a Pearson's correlation test in each comparison period between percent pale dead vegetation cover and the ratio of terns counted in the aerial imagery to nests counted on the ground (i.e. aerial count divided by ground count) for all plots containing ≥10 nests. Finally, we used a paired-samples t-test to determine if colony disturbance levels were overall different between flights and control periods.

Results

Ground nest counts in comparison plots on 17 June recorded a total of 769 nests among the 40 plots used for comparison (range = 0–68 nests/plot), compared to 703 terns (91.4% of ground count; range = 1–69 terns/plot) counted in the same plots extracted from the aerial imagery. On 21 June, 845 total nests were counted on the ground in 43 plots (range = 0–68 nests/plot), compared to 802 terns (94.9% of ground count; range = 0–72 terns/plot) counted in the aerial imagery from 22 June. On 25 June, 806 nests were counted on the ground in 45 plots (range = 0–60 nests/plot), compared to 782 terns (97.0% of ground count; range = 0–66 terns/plot) counted in the aerial imagery. Linear regressions between the two count methods were very strong and showed similar coefficients in all three comparison periods (Fig. 5), although the coefficient increased slightly in each successive period: $\beta_{\text{17 June}} = 0.928$ (95% CI = 0.897–0.959, $F_{1,39} = 3647.329$, $P < 0.001$, $R^2 = 0.989$); $\beta_{\text{21–22 June}} = 0.966$ (95% CI = 0.931–1.001, $F_{1,42} =$

3107.002, $P < 0.001$, $R^2 = 0.987$); $\beta_{25\ \text{June}} = 0.977$ (95% CI = 0.927–1.027, $F_{1,44} = 1555.357$, $P <$ 0.001, $R^2 = 0.972$).

The full colony census conducted by Parks Canada on 21 June recorded 2695 nests on island 1 and 3634 nests on island 2, for a total of 6329 nests in the colony. In contrast, we counted 2539 terns on island 1 (94.2% of ground count) and 3385 terns on island 2 (93.1% of ground count), for a total of 5924 terns (93.6% of ground count), in the aerial imagery from the first flight carried out on 22 June. In the second flight, we counted 2573 terns on island 1 (95.5% of ground count) and 3379 terns on island 2 (93.0% of ground count), for a total of 5952 terns (94.0% of ground counts).

There was no significant correlation between percent pale dead vegetation cover in plots and the ratio of terns counted in aerial imagery to nests counted on the ground in any of the comparison periods (17 June: $n = 29$, $r = 0.035$, $P = 0.855$; 21–22 June: $n = 31$, $r = -0.277$, $P =$ 0.132; 25 June: $n = 33$, $r = -0.323$, $P = 0.066$), although correlations were negative as expected on 21–22 June and 25 June, and came close to statistical significance in the latter period.

Total disturbance scores across both islands averaged 4.7 (SEM = 1.3, range = 0–15) per flight over the course of the 10 flights during which disturbance levels were recorded, compared to 4.8 (SEM = 2.6, range = 0–26) per matched control period. This difference was not statistically significant ($t_9 = -0.031$, $P = 0.976$). No disturbance at all was recorded on either island during four control periods, but only during one flight. Throughout all flights we observed a total of eight panic events, compared to four throughout control periods. Finally, we observed panics shortly after the aircraft took off and first approached the colony on the first flight of the first two survey days (including 16 June when we did not record detailed disturbance data), after which this did not reoccur.

Discussion

The Tern Islands Common tern colony of Kouchibouguac National Park represents a prime example of where small UAS could be beneficial for surveying waterbird populations. The annual ground census conducted by the park, while effective, causes sustained disturbance of the large colony for several hours during peak incubation as terns flush off their nests and relentlessly mob surveyors. In addition, surveyors inadvertently trample nests, walk all over the fragile beach grass habitat and disturb a population of Red-breasted Mergansers (*Mergus serrator*) counting upwards of 80 nests throughout Tern Islands, which are known to occasionally abandon their nests following investigator disturbance (Craik and Titman 2009).

In this study, the AI-multi UAS proved effective for surveying the Tern Islands colony, yielding high-resolution aerial imagery in which tern counts were overall proportionally consistent with nest counts carried out on the ground, the former generally in the low to high 90% range of the latter. There are several potential explanations for this small but constant discrepancy that are not necessarily mutually exclusive.

First, it is possible that not all terns were detected in the aerial imagery. When performing counts, we noticed that the contrast of terns was poorer over certain backgrounds (chiefly pale dead vegetation), that they were more challenging to discern in blurrier portions of the imagery, and that their visibility appeared to be affected by lighting conditions. The 17 June imagery differed from the 22 and 25 June imagery as a result of bright, sunny sky conditions during the former day compared to overcast conditions during the latter days. This yielded very clear shots but with pronounced shadows and occasional exceedingly bright, “blown-out” areas on 17 June compared to deeper, more contrasting colors and no shadows on 22 and 25 June, which we found to make terns overall more visible on the latter days. We suspect this contributed to the distinctly lower regression coefficient with ground counts on 17 June (Fig. 5). We also tested for a relationship of greater proportional underestimation of numbers in aerial imagery compared to ground counts with increasing pale dead vegetation cover in comparison plots, finding no correlation on 17 June and weak, statistically insignificant correlations on 21–22 and 25 June. We believe that the results for the latter days nevertheless suggest the existence of the presumed relationship, while the lack of any correlation on 17 June may be due to the effect being masked by the overall poorer quality of the imagery as a result of lighting conditions.

Second, it is possible that not all nests counted on the ground were active. In a concurrent study of nesting success in the colony for which we monitored 105 nests for up to 3.5 weeks, we observed several instances where eggs remained in seemingly abandoned nests for multiple days, even weeks. Because terns are flushed off nests during ground counts, it would have been impossible to differentiate such nests from active ones. Therefore, while ground counts could be said to have recorded the total number of nesting *attempts*, UAS aerial surveys, because they were constrained to counting terns, could only record the number of active nests at any given time. Third, it is also possible that active nests were sometimes left unattended. Nest attentiveness is known to increase throughout egg-laying, from as little as 40% after the first egg is laid to ≥95% within a few days of clutch completion (Courtney 1979, Bollinger et al. 1990, Nisbet 2002). Among the 105 nests we monitored starting 15 June, 11 continued laying through subsequent checks on 18 and 21 June. Reduced attendance of incomplete clutches may therefore also have contributed to the lower regression coefficient on 17 June.

The regression coefficient increase from 21–22 June to 25 June was not as large (Fig. 5), but it is worth noting the substantial decrease in nests counted on the ground, from 885 among all 45 plots on 21 June to 806 on 25 June, whereas numbers were virtually constant from 17 to 21 June. At least part of this decrease likely resulted from underestimation, as by 25 June a significant proportion of nests had fully hatched and spotting chicks in and around nests proved more challenging than spotting eggs. In addition, surveyors were more distracted trying to avoid stepping on wandering chicks, which were often concealed in vegetation. These circumstances were especially problematic in more populous plots. Even during the first two comparison periods, nests in the two most populous plots (counting ~60–70 each) were more challenging to keep tally of using our circular survey method in which the outer surveyor scanned a total area three times as large as the inner surveyor, and we believe this is why greater numbers were counted in the aerial imagery (Fig. 5). Other instances where aerial counts of plots exceeded ground counts (once by three, twice by two, and 10 times by one) in the first two comparison periods may have been due to loafing terns or false positives.

Full island and colony counts yielded very similar aerial/ground ratios to comparison plot counts, especially when looking at the ratios for total numbers counted among all plots: 94.9%

among 43 plots in the 21–22 June comparison period compared to 93.6% (94.2% on island 1 and 93.1% on island 2) throughout the entire colony in the imagery from the first flight on 22 June and 94.0% (95.5% on island 1 and 93.0% on island 2) in the second flight. There could be a few reasons for the slightly lower ratios in full colony counts. First, for comparison plots we selected the clearest image of each plot between the two flights in order to achieve the most reliable counts possible, whereas the full colony counts were performed in the imagery of each flight separately. Second, counts in each plot focused the observer on a relatively small area that was meticulously scanned, whereas such thorough scanning of the entire area of the islands was possibly not achieved. Third, lower ratios in the full counts of island 2 compared to island 1 may suggest that underestimation of tern numbers occurred in the portions of island 2 filled in by lower resolution 122-m altitude imagery. A total of 425 (12.6% of island count) and 383 (11.3% of island count) terns were counted in these portions of imagery from the first and second flight, respectively.

Overall, our findings highlight how survey timing, subject visibility and weather conditions are important factors to consider for surveying waterbird colonies with a small UAS. For Common terns, surveys should be carried out as close as possible to the peak of the incubation period, when the proportion of completed clutches is highest but before nests begin hatching en masse, in order to capture the period of highest nest attendance by adults. Following our method and provided ideal overcast sky conditions, optimally timed UAS surveys should yield Common tern population counts in the 93–96% range of the numbers of nests that would be counted on the ground. Under sunny conditions, the ratio may drop by up to a few percentage points. It should be noted however that a superior camera may improve overall detectability of subjects. Watts et al. (2010), for example, describe a custom-built UAS capable of carrying a heavier SLR camera than the compact model we used. Furthermore, differences in size and coloration among species as well as habitat type (i.e. ground cover) may also affect detectability, as was noted by Chabot and Bird (2012). Nest attendance behavior, nesting synchrony and loafing behavior may also vary among species. Finally, entirely different considerations may apply to UAS surveys of gregarious waterbirds in non-breeding situations, such as foraging or migratory flocks. A major advantage of small UAS is that repeated surveys can be conducted at relatively little extra cost or effort in order to assess and control for such factors (Sarda-Palomera et al. 2012). As has been ongoing for several decades with regard to conventional aerial surveys, further studies of UAS survey accuracy of different species, in different systems and under different circumstances will be necessary if the method continues to gain traction.

Regarding disturbance, we found no statistically significant evidence that the UAS caused more overall disturbance to the colony over the course of 10 flights than during matched control periods when the aircraft was not airborne, although anecdotal evidence suggests that the UAS likely caused some limited disturbance. It is generally difficult to objectively quantify disturbance levels across a large tern colony, and we opted for a simple scoring scheme at fixed time intervals because we felt that added complexity might just compound subjective assumptions. Disturbance and agitation in Common tern colonies are common even in the absence of investigators; causes include fighting among neighboring individuals as well as the presence of terrestrial or avian predators. Although panics are often caused by the latter, they also regularly occur for no discernible reason (Morris and Wiggins 1986, Burger and Gochfeld 1991, Nisbet 2002). We observed a total of eight panics throughout flights compared to four during control periods, which may suggest the aircraft was occasionally the cause, but we believe the most compelling evidence for disturbance by the UAS were the panics observed immediately following takeoff on the first flight of the first two survey days but not thereafter. This would seem consistent with a pattern of habituation (Nisbet 2000) whereby the terns were initially alarmed by a novel stimulus but subsequently stopped reacting as the aircraft regularly reappeared over a period of several days and repeatedly flew over the colony without adverse consequences. In any case, it can be confidently stated that the UAS caused far less disturbance than the conventional ground census of the colony.

In conclusion, this study provides the most comprehensive evidence to date that small UAS can be effectively employed for fine-scale, low-disturbance monitoring of waterbirds. We have demonstrated how such an aircraft can be used to conduct a reliable population census of a large Common tern colony that otherwise requires substantial time, effort and disturbance to census on the ground. We encourage waterbird researchers and managers to consider taking advantage of UAS in similar situations elsewhere. As they become more widespread and accessible, UAS are anticipated to play increasingly frequent and varied roles in biological research and management (Watts et al. 2010, Koh and Wich 2012, Anderson and Gaston 2013), and useful overviews of current UAS technology in the context of scientific research are provided by Watts et al. (2012) and Anderson and Gaston (2013). Another important consideration for prospective UAS users is airspace regulations, which can be restrictive or prohibitive in most developed countries, although many governments are now working rapidly to update regulations in order to better accommodate UAS, recognizing the inevitability of their proliferation (Dalamagkidis et al. 2008, Rango and Laliberte 2010, Mulac 2011).

Acknowledgements

We thank G. Maillet for much assistance in all aspects of data collection, E. Tremblay for logistical and administrative assistance, D. Saunders and L. Laltoo for GPS data collection and GIS assistance, G. Lewis for assistance with UAS test flights prior to field work and C. Tataryn for UAS support during field work, R. Titman for general assistance with study design and preliminary trials, and B. Martin, G. Daigle and D. MacDonald for facilitating field work. UAS flights were authorized by Transport Canada in accordance with a Special Flight Operation Certificate (#12007), and the study was authorized by a Parks Canada Agency Research and Collection Permit (#KOU-2012-10913) as well as a McGill University Animal Use Protocol (#5394). Funds and in-kind contributions were provided by the Kenneth M. Molson Foundation, the New Brunswick Wildlife Trust Fund, the Canadian Wildlife Federation, Parks Canada, Aerial Insight, MicroPilot, and the Fonds Québécois de la Recherche sur la Nature et les Technologies.

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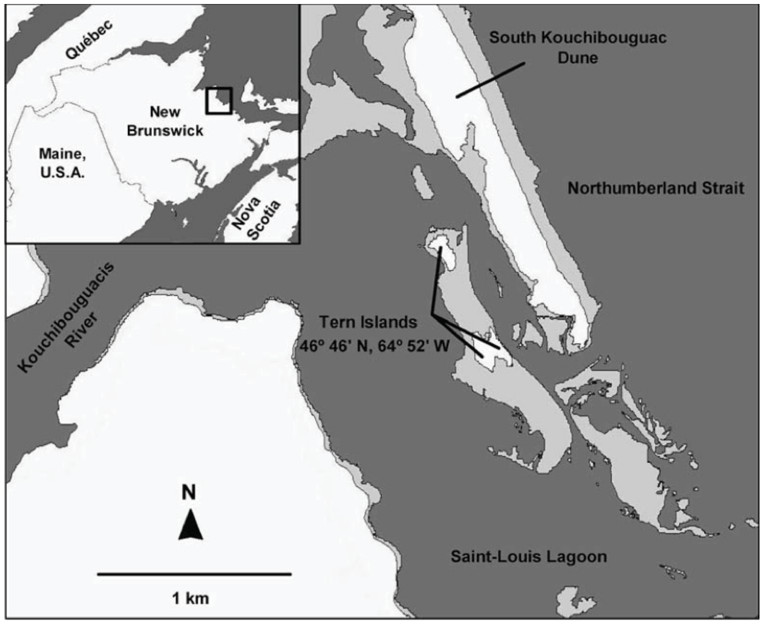

Figure 1. Map of Tern Islands study site in Kouchibouguac National Park, New Brunswick, Canada. Light grey areas represent intertidal zones (from Craik and Titman 2009).

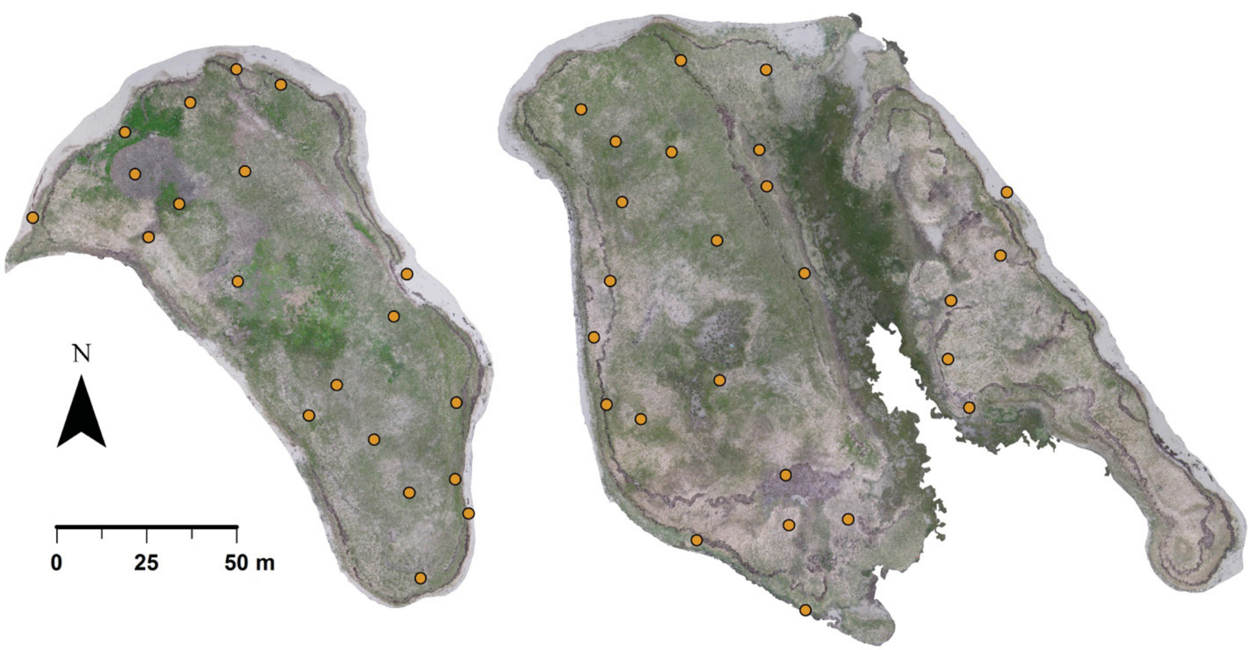

Figure 2. Locations of 5-m radius plots used to compare aerial Common tern counts from a small unmanned aircraft system (UAS) to ground nest counts throughout the Tern Islands colony (left: island 1; right: island 2), Kouchibouguac National Park, New Brunswick, 2012. Island imagery was constructed from seamless blending of overlapping UAS aerial photos taken from a 91-m altitude with a spatial resolution of ~3 cm/pixel.

Figure 3. The hand-launched AI-multi electric unmanned aircraft prior to takeoff from the South Kouchibouguac Dune, Kouchibouguac National Park, New Brunswick, 2012.

Figure 4. Example aerial images (~3 cm/pixel) of 5-m radius plots used to compare Common tern counts from a small unmanned aircraft to ground nest counts on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012. Thirty terns were counted in the plot to the left and 36 in the plot to the right.

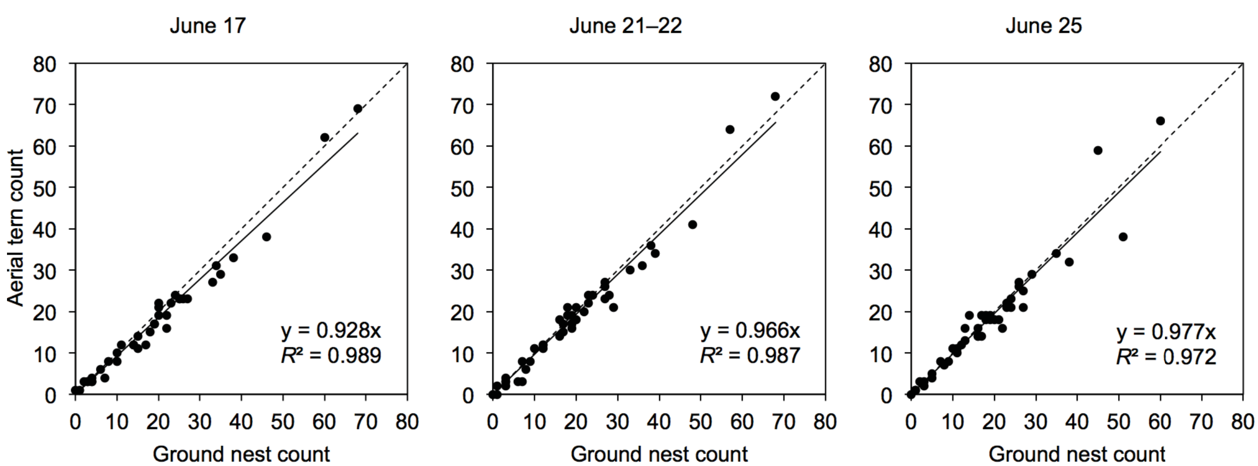

Figure 5. Linear regressions between aerial Common tern counts from a small unmanned aircraft and ground nest counts in 5-m radius plots in three comparison periods (17 June: n = 40; 21–22 June: n = 43; 25 June: n = 45) on Tern Islands, Kouchibouguac National Park, New Brunswick, 2012.

SUMMARY AND CONCLUSIONS

The aim of this thesis was to produce information that will help stimulate and guide the adoption of emerging unmanned aircraft technology in the field of wildlife science. Specifically, I sought to provide: (1) a detailed review of potential applications for UAS throughout the discipline, (2) rigorous method validation studies, and (3) demonstrations of fully integrated use of UAS in relevant, management-driven wildlife research studies.

Chapter 1 fulfils the first objective as the first comprehensive wildlife-specific review of potential UAS applications, focusing on which types of species are most likely to lend themselves to UAS-based data collection, and with conclusions empirically supported by a systematic review of the primary wildlife literature. In this manner, it was determined that there is strong potential for small fixed-wing UAS to perform small-scale surveys of waterbirds and certain mammals that congregate in predictable locations, and for small rotary-wing UAS to observe animals up-close in hard-to-reach places. Moreover, small UAS will tend to be beneficial for wildlife habitat sensing in a variety of situations where timely, fine-scale data are required in areas that are impractical to survey at ground level due to size and/or ruggedness. Finally, upcoming UAS-based automated telemetry tracking promises to facilitate monitoring of animals that occupy small to medium home ranges in rugged habitats where GPS-based tracking is inadequate, or animals that are too small to carry GPS-based tracking devices.

The second and third thesis objectives are both fulfilled in each of the two case studies presented in Chapters 2–3 (focused on the least bittern) and 4–5 (focused on the common tern). Chapter 2 provides a detailed appraisal of the fine-scale habitat sensing capacity of a small UAS and an attestation of its benefits for studying species in hard-to-navigate habitats such as wetlands. This capacity is then successfully exploited to provide key data in a habitat study of the least bittern in Chapter 3 and of the common tern in Chapter 4. Finally, Chapter 5 provides a rigorous validation of the capacity of a small UAS to remotely census a colonial waterbird species, highlighting its benefits for unobtrusive monitoring of highly sensitive species such as the common tern. It represents the most thorough evaluation to date of a UAS for surveying animals.

This thesis presents the first standard, biology-oriented wildlife studies to integrate a UAS as a component of the data collection methods. The least bittern study determined that wetland habitat quality in a designated critical breeding site is optimized by a combination of abundant cattail cover and high water-vegetation edge density. This finding will be key in the upcoming creation of a site management plan for this federally protected species. The common tern study uncovered numerous breeding habitat relationships in a major colony situated on a geologically precarious coastal island complex, namely strong affinity for washed-up eelgrass, preference for higher elevation, avoidance of sandy beach areas and preference for nesting near forbs. These findings will be of value should on-going island erosion or rising sea level threaten the colony to the point that habitat management initiatives become necessary.

The precedents provided by the case studies as well as the additional applications proposed in the review suggest considerable potential for UAS to contribute to wildlife research and management as precise, convenient, timely and discreet remote sensing devices. Although regulatory barriers currently limit their application, these are likely to be alleviated in the near future. From a technological standpoint, currently available UAS have the necessary capacities to perform small-scale visual observation and surveys of wildlife as well as habitat sensing. For wildlife telemetry tracking, proof-of-concept field trials should be undertaken in order to better evaluate the feasibility of this application. I encourage wildlife practitioners to generally familiarize themselves with burgeoning UAS technologies and keep abreast of their on-going development.