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REVIEW

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Automated detection of wildlife using drones: Synthesis, opportunities and constraints

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Abstract

1. Accurate detection of individual animals is integral to the management of vulnerable wildlife species, but often difficult and costly to achieve for species that occur over wide or inaccessible areas or engage in cryptic behaviours. There is a growing acceptance of the use of drones (also known as unmanned aerial vehicles, UAVs and remotely piloted aircraft systems, RPAS) to detect wildlife, largely because of the capacity for drones to rapidly cover large areas compared to ground survey methods. While drones can aid the capture of large amounts of imagery, detection requires either manual evaluation of the imagery or automated detection using machine learning algorithms. While manual evaluation of drone-acquired imagery is possible and sometimes necessary, the powerful combination of drones with automated detection of wildlife in this imagery is much faster and, in some cases, more accurate than using human observers. Despite the great potential of this emerging approach, most attention to date has been paid to the development of algorithms, and little is known about the constraints around successful detection (P. W. J. Baxter, and G. Hamilton, 2018, *Ecosphere*, **9**, e02194).
2. We reviewed studies that were conducted over the last 5 years in which wildlife species were detected automatically in drone-acquired imagery to understand how technological constraints, environmental conditions and ecological traits of target species impact detection with automated methods.
3. From this review, we found that automated detection could be achieved for a wider range of species and under a greater variety of environmental conditions than reported in previous reviews of automated and manual detection in drone-acquired imagery. A high probability of automated detection could be achieved efficiently using fixed-wing platforms and RGB sensors for species that were large and occurred in open and homogeneous environments with little vegetation or variation in topography while infrared sensors and multirotor platforms were necessary to successfully detect small, elusive species in complex habitats.
4. The insight gained in this review could allow conservation managers to use drones and machine learning algorithms more accurately and efficiently to conduct abundance data on vulnerable populations that is critical to their conservation.

KEYWORDS

drones, machine learning, remote sensing, thermal imaging, UAVs, unmanned aerial vehicles, wildlife detection

1 | INTRODUCTION

Effective management of vulnerable wildlife species relies on regular detection and counting of populations to monitor trends, particularly in response to interventions (Renwick et al., 2011). However, it has proven difficult to accurately detect species that are widely dispersed and occur in difficult to access areas (Hollings et al., 2018; Kellenberger et al., 2018). Aerial surveys are commonly used to detect and count species which fit these criteria, but they can be logistically challenging to conduct due to the expense of operating manned aircraft and expertise needed to do so safely (Anderson & Gaston, 2013; Terletzky & Koons, 2016). Manned aircraft surveys have also been shown to lead to inaccurate results when surveying species that engage in cryptic behaviours or inhabit heterogeneous environments with complex vegetation structure (Hollings et al., 2018; Kellenberger et al., 2018). It has been suggested that this is due to a lack of contrast between individual animals and their background environment, leading to a high proportion of individuals going undetected (Hollings et al., 2018; Kellenberger, Marcos, Courty, et al., 2018).

Over the last decade, there has been an increase in the use of drones (also known as unmanned aerial vehicles, UAVs and remotely piloted aircraft systems, RPAS) to detect wildlife that had previously been surveyed using conventional light aircraft (Anderson & Gaston, 2013; Andrew & Shephard, 2017; Colefax et al., 2018; Hodgson et al., 2018; Hollings et al., 2018). A variety of sensors that can be attached to drones and they are capable of collecting higher resolution images and flying lower than conventional aircraft (Anderson & Gaston, 2013; Andrew & Shephard, 2017; Colefax et al., 2018; Hodgson et al., 2018; Hollings et al., 2018). All of these factors make it possible to detect smaller species with drones than can be accurately identified from manned aircraft as well as cryptic species and animals that are partially obscured by features of their habitat (Christie et al., 2016). Operating a drone also costs less and poses less risk to researchers than using manned aircraft, and drones can cover large and inaccessible areas unsuited to traditional ground surveys (Christie et al., 2016). Despite the increased interest in and uptake of drones by ecologists, there has been little investigation into how to plan drone surveys to detect wildlife using automated methods efficiently and accurately (Baxter & Hamilton, 2018; Linchant et al., 2015). Although manual analysis of images has been used in the majority of drone wildlife detection studies, there has been an emerging trend of using machine learning techniques to automatically identify wildlife in imagery from drones (Hodgson et al., 2016; Seymour et al., 2017). Automated methods have the potential to reduce the number of animals missed in surveys and the time taken to complete image analysis compared to manual methods, improving both the accuracy and efficiency of detection (Chen & Liu, 2017; Hodgson et al., 2018; Maiti et al., 2015; Martin et al., 2012; McCafferty et al., 2015; Norouzzadeh et al., 2018; Rey et al., 2017; Xue et al., 2017).

While there have been reviews of drone wildlife survey methods (Chabot & Francis, 2016; Hollings et al., 2018; Linchant et al., 2015), they have provided very little information on the challenges unique to the automated detection of animals from this kind of imagery. A review of automated detection of wildlife in remotely sensed imagery by Hollings et al. (2018) reported on a single study that used these methods. Reviews on the use of drones for wildlife surveys (Chabot & Francis, 2016; Linchant et al., 2015) also found a very small number of studies which combined drones with automated detection. This study concluded that it had only been shown to be effective for stationary colonies of white birds on unobstructed beaches (Chabot & Francis, 2016; Linchant et al., 2015). There has been considerable progress made in the refinement and testing of machine learning algorithms specifically for detecting wildlife in drone-acquired imagery since these reviews were conducted, as well as improvements in the resolution of both colour and infrared sensors that can be mounted on drones (Chrétien et al., 2016; Corcoran et al., 2019; Hodgson et al., 2016; Kellenberger, Marcos, & Tuia, 2018; Seymour et al., 2017). It is thus apparent that automated detection could be applied to a wider variety of species in more complex and varied environments, with similar or greater accuracy than previously reported (Chrétien et al., 2016; Hodgson et al., 2016; Kellenberger, Marcos, & Tuia, 2018; Seymour et al., 2017). However, there is currently a lack of synthesis of knowledge on how to achieve this (Chrétien et al., 2016; Corcoran et al., 2019; Hodgson et al., 2016; Kellenberger, Marcos, & Tuia, 2018; Seymour et al., 2017).

This literature review synthesises the progress that has been made in the development of methods for detecting wildlife in drone-acquired images since 2015. We evaluated the performance of different automated detection methods, using images of various species with different ecological traits, under a range of environmental conditions, and collected using different drone platforms and sensors. From this, we make recommendations for the design of future surveys to automatically detect a wide range of wildlife with optimal accuracy and efficiency. We also identify the knowledge gaps in this area that need to be investigated to gain the most benefit for conservation from these emerging wildlife detection technologies.

2 | MATERIALS AND METHODS

A survey of available literature in which animals were detected using automated methods in drone-acquired images was conducted using Scopus and Web of Science. The keywords 'unmanned aerial vehicle', 'uav', 'uas', 'remotely piloted aircraft', 'rpas', 'drone', 'wildlife', 'monitor*', 'detect*', 'automated' and 'census' were applied to search these databases. Searches took place in November 2020, with a data limit set from January 2015 to the current day to capture the recent developments that have been made in applying machine-learning-based image detection to images captured with drone platforms. Conference articles were included, but unpublished reports and theses were not.

3 | RESULTS AND DISCUSSION

A total of 19 studies published since 2015 in which wildlife species were automatically detected in images acquired from drones were identified and reviewed, with five studies applying modified automated detection methods to the same dataset. The traits of target species surveyed with drones and detected using automated methods are summarised in Table 1. The flight specifications, environmental conditions, automated detection method use and probability of detection found in these studies are summarised in Table 2.

3.1 | Size, colour and dispersion of target species

In contrast to the findings of previous reviews, automated methods were most often used to detect terrestrial mammals (10 studies), followed by birds (6 studies), marine mammals (2 studies) and arboreal mammals for which one study had been conducted (Table 1). In earlier work, automated detection of arboreal mammals represented

TABLE 1 Traits of target species detected with automated methods in images from drone surveys since 2015 (*Studies using the same dataset)

Study	Type of target species	List of target species	Body size of target species (kg)	Species distribution pattern	Body temperature of target species (°C)
Corcoran et al. (2019)	Arboreal Mammal	Koala *Phascolarctos cinereus*	4–15	Random	36.6
Afan et al. (2018)	Bird	Glossy Ibis *Plegadis falcinellis*	0.43	Uniform	N/A
Francis et al. (2020)		African Openbill *Anastomus lamelligerus*, African Sacred Ibis *Threskiornis aethiopicus*, Egret sp. *Egretta* sp., Marabou Stork *Leptoptilos crumeniferus*, Pink-backed Pelican *Pelecanus rufescens*, Yellow-billed Stork *Mycteria ibis*, Australian White Ibis *Threskiornis molucca*, Straw-necked Ibis *Threskiornis spinicollis*	1.1–8	Uniform	N/A
Hodgson et al. (2018)		Decoys simulating Greater Crested Tern *Thalasseus bergii*	0.34	Uniform	N/A
Hong et al. (2019)		Spot-billed duck *Anas poecilorhyncha*, green-winged teal *Anas crecca*, great egrets *Ardea alba*, grey heron *Ardea cinerea*	0.79–1.5	Uniform	N/A
Liu et al. (2015)		Black-faced spoonbills *Platalea minor*	1.2–1.5	Uniform	N/A
Rush et al. (2018)		Lesser Black-backed Gulls *Larus fuscus*	0.77	Uniform	N/A
Gorkin et al. (2020)	Marine mammal	Sharks	520–1,100	Random	N/A
Seymour et al. (2017)		Grey seal *Halichoerus grypus*	14–310	Clumped	38.9
Chrétien et al. (2015)	Terrestrial mammal	American Bison *Bison bison*, Elks *Cervus canadensis* fallow deer *Dama dama*, grey wolf *Canis lupus*	30–1,000	Clumped	38.7–40
Chrétien et al. (2016)		White-tailed deer *O. virginianus*	40–136	Clumped	38.6
Kellenberger et al. (2017)* Kellenberger, Marcos, and Tuia (2018)* Kellenberger, Marcos, Courty, et al. (2018)* Kellenberger et al. (2019)* Rey et al. (2017)*		Common Elands *Taurotragus oryx*, Greater Kudus *Tragelaphus strepsiceros*, Gemsboks *Oryx gazella*, Hartebeests *Alcelaphus buselaphus*, Gnus *Connochaetes gnou* and *Connochaetes taurinus*, Blesboks *Damaliscus albifrons*, Springboks *Antidorcas marsupialis*, Steenboks *Raphicerus campestris*, Common Duickers *Sylvicapra grimmia*, Impalas *Aepyceros melampus*, Burchell's Zebras *Equus quagga burchellii*, Ostriches *Struthio camelus australis* and Giraffes *Giraffa camelopardalis giraffa*	12–800	Clumped	N/A
Lhoest et al. (2015)		Hippopotamus *Hippopotamus amphibius* L.	1,300–1,500	Clumped	36.1
Longmore et al. (2017)		Cows *Bos Taurus*	272–454	Clumped	38.6
Oishi et al. (2018)		Sika deer *Cervus nippon*	66–154	Clumped	37.5

TABLE 2 Flight and sensor specifications, environmental and weather conditions, detection method and probability of automatically detecting wildlife in images from drone surveys conducted since 2015 (*Studies using the same dataset)

Study	Platform type	Sensor type	Flight height above ground (m)	Flight speed (km/hr)	Ground resolution (cm/pixel)	Ambient temperature during surveys(°C)	Wind speed (km/hr)	Weather conditions	Habitat	Canopy cover	Automated detection method	Probability of detection (%)
Afan et al. (2018)	Multirotor	RGB	50	12	1.32	N/A	14.4	Fine	Semi-artificial ponds	Low	Supervised pixel-based image classification	43–49
Chrétien et al. (2015)	Multirotor	RGB and Infrared	60	18–35	0.8–5.4	Not stated	19	Fine	Wildlife enclosures	Low	OBIA	50–100
Chrétien et al. (2016)	Multirotor	RGB and Infrared	60	22	0.8–5.4	Not stated	Not stated	Not stated	Wildlife enclosures	Low	Supervised pixel-based image classification, Unsupervised pixel-based image classification	32–52
Corcoran et al. (2019)	Multirotor	Infrared	60	8	7–13.7	8.0–21.7	6–17	Not stated	Eucalypt forest	Low-Dense	CNNs	68–100
Francis et al. (2020)	Multirotor	RGB	20–70	7.2–36	0.66–2.3	N/A	Not stated	Not stated	Floodplain	None	Supervised pixel-based image classification	91–98
Gorkin et al. (2020)	Blimp	RGB	60	N/A (Tethered platform)	Not stated	N/A	<30	Fine	Marine	None	CNNs	91.67
Hodgson et al. (2018)	Multirotor	RGB	30–120	N/A (Hovering in place while images collected)	0.82–3.29	N/A	9–37	Fine	Beach	None	Support vector machine	92–98
Hong et al. (2019)	Multirotor	RGB	100	Not stated	0.01	N/A	Not stated	Fine	Lake	None	CNNs	100

(Continues)

TABLE 2 (Continued)

Study	Platform type	Sensor type	Flight height above ground (m)	Flight speed (km/hr)	Ground resolution (cm/pixel)	Ambient temperature during surveys(°C)	Wind speed (km/hr)	Weather conditions	Habitat	Canopy cover	Automated detection method	Probability of detection (%)
Kellenberger et al. (2017)*	Fixed-wing	RGB	120–160	Not stated	4	N/A	Not stated	Not stated	Grassland	None	CNNs	74
Kellenberger, Marcos, and Tuia (2018)*												30–90
Kellenberger, Marcos, Courty, et al. (2018)*												90
Kellenberger et al. (2019)*												83.72
Lhoest et al. (2015)	Fixed-wing	Infrared	38–155	Not stated	Not stated	N/A	Not stated	Fine	River	None	Supervised pixel-based image classification	75
Liu et al. (2015)	Fixed-wing	RGB	200–300	Not stated	~1.3	N/A	Not stated	Fine	Coastal wetland	None	Unsupervised pixel-based image classification	43–99
Longmore et al. (2017)	Multirotor	Infrared	120	54	Not stated	15–20	Not stated	Fine	Grassland	None	CNNs	100
Oishi et al. (2018)	Multirotor	Infrared	30	Not stated	5	Not stated	Not stated	Fine	Grassland	Moderate	Detection moving wild animals (DWA) algorithm	77.3
Rey et al. (2017)*	Fixed-wing	RGB	120–160	Not stated	4	N/A	Not stated	Not stated	Grassland	None	Support vector machine	75
Rush et al. (2018)	Multirotor	RGB	40–55	3–4	29.9	N/A	<24	Not stated	Cliff tops	None	Supervised pixel-based image classification	76–98
Seymour et al. (2017)	Fixed-wing	RGB and Infrared	Not stated	37–57	2–8	5.5–9	<45	Not stated	Rocky shoreline	None	Spectral thresholding	67–98

a frontier that had not yet been explored (Chabot & Francis, 2016; Hollings et al., 2018; Linchant et al., 2015). This is likely because canopy cover negatively impacted the probability of detections from drones. Advancements in automated detection methods such as the ability to fine-tune CNNs with a small training dataset and the increased resolution of infrared sensors may explain why detections of these species are now feasible in some cases (Chen & Liu, 2017; Corcoran et al., 2019; Halstead et al., 2018; Tang et al., 2017).

Species automatically detected in drone-acquired imagery ranged in size from the greater crested tern (Hodgson et al., 2018) with an average body weight of 0.34 kg to the common hippopotamus with an average adult male body weight of 1,500 kg (Lhoest et al., 2015) (Table 1). This is a greater size range than in surveys using drones prior to 2015 (Linchant et al., 2015). At that point, this method was not typically used for species that weighed less than 10kg due to an inability to capture images from drones at high enough ground resolution to detect species below this threshold (Linchant et al., 2015).

Species surveyed in RGB tended to be white, black or dark brown in colour against a green, grey or light brown background creating high contrast and reducing the likelihood of missing animals or misidentifying habitat features as animals (Afan et al., 2018; Chrétien et al., 2015, 2016; Hodgson et al., 2018; Hong et al., 2019; Kellenberger, Marcos, Courty, et al., 2018; Kellenberger et al., 2017, 2019; Kellenberger, Marcos, & Tuia, 2018; Liu et al., 2015; Rey et al., 2017; Rush et al., 2018).

Most species surveyed displayed clumped distribution with terrestrial mammal species moving or standing in herds, and Grey seal breeding colonies forming stationary, closely clustered groups (Table 1). In contrast to studies with manual detection, this clumping did not seem to negatively impact the probability of detecting individuals or the ability to identify them at the species level (Gentle et al., 2018; Witczuk et al., 2017). Many species surveyed such as white-tailed deer, fallow deer and impalas also had the potential to move fast in surveys, which in some cases was found to increase the likelihood of duplicate detections due to the shifting position of animals in images (Chrétien et al., 2015, 2016; Kellenberger et al., 2019). However, incorporating algorithmic tracking mechanisms into the automated methods was found to decrease duplicate detections (Corcoran et al., 2019; Oishi et al., 2018). All bird species surveyed lived in colonies with uniform dispersion (Table 1), which was noted as an advantage for automated detection in drone-acquired imagery, as it meant they were dispersed in a relatively uniform pattern where birds occurred close together making them easier to recognise than isolated individuals but the number of individuals in groups was still relatively simple to distinguish (Afan et al., 2018; Hodgson et al., 2018; Hong et al., 2019; Rush et al., 2018).

3.2 | Platforms and sensors

Studies used small platforms weighing less than 10 kg and although they appear evenly split in the use of multirotor and fixed-wing platforms, after accounting for the five studies that used the same survey data, it is apparent that multirotor drones were used more often, with 10 unique survey campaigns compared to 4 that used fixed-wing platforms and one study which used a tethered blimp (Table 2). Multirotor drones offer greater control over flight planning with the ability to manoeuvre the vehicle in closely spaced transects or grid patterns and hover in place, all of which lends them to more thorough surveys of elusive or cryptic species that may be partially obscured from view (Niethammer et al., 2012). Multirotor drones can also be flown lower than fixed-wing drones allowing for a higher ground resolution, in one case up to 0.01 cm per pixel (Hong et al., 2019) compared to a maximum ground resolution of 2 cm per pixel using fixed-wing platforms (Seymour et al., 2017) (Table 2). When fixed-wing platforms were used, they were flown higher above the ground (38–300 m) and at higher speeds (37–57 km/hr) compared to multirotor platforms (20–120 m above ground, 3–54 km/hr) (Table 2). This, along with the extended battery life of fixed-wing platforms, enabled them to be flown over larger areas, such as 103 km^2 of African savanna (Kellenberger, Marcos, Courty, et al., 2018; Kellenberger et al., 2017, 2019; Kellenberger, Marcos, & Tuia, 2018; Rey et al., 2017), and long distances over water (Lhoest et al., 2015).

Probability of detection was slightly higher in multirotor studies with some reporting a maximum of 100% detection in surveys (Chrétien et al., 2015; Longmore et al., 2017). For fixed-wing surveys with high probability of detection, there were also a large number of false detections for each confirmed true detection, with over 20 false-positive results yielded for every true-positive result in some cases (Kellenberger, Marcos, Courty, et al., 2018; Kellenberger et al., 2017, 2019; Kellenberger, Marcos, & Tuia, 2018; Rey et al., 2017). However, this false-positive rate has been attributed to low density of animals across sites surveyed rather than the type of platform used because most false-positive results came from the large volume of images collected without any animals present within them. (Kellenberger, Marcos, & Tuia, 2018; Rey et al., 2017). For multirotor designs with greater image overlap, duplicate detections of the same individuals were highlighted as the biggest challenge to achieving accurate counts of species (Chrétien et al., 2015, 2016).

Nine unique survey campaigns used RGB sensors to collect images, while four used infrared cameras and two used and compared both sensor types (Table 2). While there was a considerable overlap in the size of species surveyed with both types of sensor, only RGB sensors were used to survey species with an average body size of less than 4 kg which included several species of waterbirds with the smallest being decoys that simulated Greated Crested Tern weighing 0.34 kg (Afan et al., 2018; Francis et al., 2020; Hodgson et al., 2018; Hong et al., 2019; Liu et al., 2015; Rush et al., 2018) (Table 1). Conversely, they have mostly been used to survey relatively large species such as hippopotami, cows and American bison (Chrétien et al., 2015; Lhoest et al., 2015; Longmore et al., 2017) (Table 1). This may be due to the higher ground resolution possible with RGB sensors (up to 0.01 cm per pixel) compared to infrared sensors (up to 4 cm per pixel) (Table 2). Birds were only surveyed with RGB sensors, while koalas were the only arboreal mammal surveyed and this was conducted with an infrared sensor (Table 1). This is likely due to the bird species surveyed generally occurring in relatively homogenous habitat with no canopy cover (Afan et al., 2018; Francis et al., 2020; Hodgson et al., 2018; Hong et al., 2019; Rush et al., 2018), meaning they were easily detectable using the visible spectrum, compared to the koalas surveyed by Corcoran et al. (2019) which tended to be occluded by canopy. In infrared imaging, the heat given off by the koalas was visible even in cases where individuals were partially covered by branches, therefore increasing probability of detection in more heterogeneous habitats with dense vegetation (Corcoran et al., 2019).

3.3 | Environmental conditions

Almost all surveys of terrestrial mammals with drones were conducted in areas with low or no canopy cover and relatively flat topography (Table 2). This is likely because higher canopy cover can occlude animals from view of the sensor (Witczuk et al., 2017) and greater variation in topography is likely to result in the animals appearing as different sizes in images, making it more difficult for algorithms to correctly classify species (Rey et al., 2017). However, studies by Corcoran et al. (2019) and Oishi et al. (2018) found a high probability of detection was possible in areas with moderate or dense canopy cover. These studies used infrared sensors which were found to partially mitigate the impact of canopy cover as the heat signatures of animals were still distinguishable even when they were partially obscured by canopy (Corcoran et al., 2019; Oishi et al., 2018). However, since neither study directly measured canopy cover, the scale of its impact on detection is unknown, and further studies are required to quantify the potential impact of this variable (Corcoran et al., 2019; Oishi et al., 2018). The two studies conducted by Chrétien et al. (2015, 2016) and on automated detection of non-arboreal terrestrial mammals (American bison, elks, fallow deer, grey wolf and white-tailed deer) were both conducted in semi-artificial environments in wildlife enclosures with small sample sizes; therefore, it remains unknown how automated detection would perform in surveys of large populations of these species in their natural habitats (Table 1).

Surveys were conducted in fine and dry conditions (Table 2). This is unsurprising as flying in rain has been shown to increase risk of loss of control of the drone (Ranquist et al., 2017). Wind speeds of over 19 km/hr lowered the stability of multirotor platforms or rendered them impossible to fly (Chrétien et al., 2015), while fixed-wing drones flown in winds up to 45 km/hr with no issues reported (Seymour et al., 2017). It was also noted in some studies that motion blur due to wind led to a decreased probability of automated detection, as the outlines and features of target species were less clearly distinguishable from background noise (Chrétien et al., 2015, 2016; Oishi et al., 2018). In one RGB survey study by Liu et al. (2015), sun was mentioned as an issue as the reflections of the sun off the water were often the same size and shape as the Black-faced spoonbills targeted for detection.

Infrared imaging surveys were generally carried out in the coldest seasons of the year and coldest times of the day (most often the early hours of the morning) to ensure the highest possible contrast between the heat signatures of the target animals and the temperature of their environment (Corcoran et al., 2019; Lhoest et al., 2015; Longmore et al., 2017). The body temperature of terrestrial mammals during surveys with thermal infrared sensors was between 36.1 and 38.9°C, and there was a contrast between the target animals and the background temperature of 14.4 and 33.1°C (Table 1). In all cases, this contrast was found to be sufficient to enable identification of targets at the species level (Chrétien et al., 2015, 2016; Corcoran et al., 2019; Lhoest et al., 2015; Longmore et al., 2017; Oishi et al., 2018; Seymour et al., 2017). For marine species, although the target species of seal maintained a stable deep body temperature (Worthy, 1991), their external temperature varies with exposure to different air and water temperatures (Mauck et al., 2003; McCafferty et al., 2005). This required temperature thresholds to be set at specific study sites for infrared image capture, based on ambient and surface temperatures (Seymour et al., 2017), for example 9°C and 5.5°C in Nova Scotia, Canada.

3.4 | Automated detection methods

Few studies published before 2015 used automated methods to detect wildlife in drone surveys, and the details of the approaches used in these studies are summarised in previous literature reviews by Chabot and Francis (2016) and Linchant et al. (2015). Prior to 2015, most studies which attempted automated detection of wildlife in drone-acquired imagery used simple spectral thresholding approaches (Chabot & Francis, 2016). Animal pixels were differentiated from non-animal pixels based on whether the spectral value of the pixel was above or a below a set threshold (Chabot & Francis, 2016). For example, light/dark spectral thresholds have been used to identify white birds on dark backgrounds in RGB (Chabot & Bird, 2012) and between hot rabbits and a cold background in infrared imagery (Christiansen et al., 2014), while blue/green thresholds have been used to distinguish between marine mammals and water (Podobna et al., 2010; Schoonmaker et al., 2010, 2011; Selby et al., 2011). Some earlier studies (pre-2015) introduced size and shape as an identifying feature in template-matching approaches in which the degree to which an object matched the size, shape and colour of sample images of the target animal was used to classify them (Abd-Elrahman et al., 2005; Christiansen et al., 2014). However, even with this additional layer of complexity, these simple thresholding and template-matching methods relied on a very high contrast on which to base the threshold and very high level of consistency in both animal and background pixels (Chabot & Francis, 2016). This means that the method was only accurate for counting animals with very little variation in colour, temperature, shape and size on very homogeneous backgrounds (Chabot & Francis, 2016).

A small number of studies published before 2015 used more advanced machine learning approaches to automatically detect animals in drone-derived imagery. One study by Grenzdorffer (2013) used supervised pixel-based classification, in which images were classified as one of the seven different classes of bird based on their similarity to manually traced training images. This allowed for detection of birds with greater phenotypic variation on more heterogeneous backgrounds than simple spectral thresholding and template-matching, but with less clear-cut results due to a large degree of overlap between image classes necessitating time-consuming post-classification procedures to determine the correct label for images that matched multiple classes (Grenzdorffer, 2013).

Object-based image analysis (OBIA) was also used in a small number of studies prior to 2015. As opposed to supervised classification in which whole images were labelled as containing a particular target animal or not, OBIA involves algorithmic segmentation of spectrally similar pixels into a mosaic of adjoining objects which each receive their own classification (Maire et al., 2013; Mejias et al., 2013). This allowed for automated detection of sparsely dispersed animals in large photo sets, as opposed to the small numbers of photos with densely clustered sea birds or marine mammals that could be analysed with simple spectral thresholding and template-matching approaches (Maire et al., 2013; Mejias et al., 2013).

Methods that were used prior to 2015 that continued to be used in subsequent studies were supervised pixel-based image classification which was used in five studies, OBIA which was used in two studies and spectral thresholding which was used in one study (Table 1). Supervised pixel-based image classification approaches were found to result in accurate counts of Lesser Black-backed Gulls and hippopotami in homogeneous environments with no obstructing vegetation (Lhoest et al., 2015; Rush et al., 2018) but resulted in low accuracy when Glossy Ibis in vegetation of over a metre (Afan et al., 2018) and white-tailed deer in forests (Chrétien et al., 2016). OBIA was found to result in higher detection probability than both supervised and unsupervised pixel-based image classification for white-tailed deer in forested habitats (Chrétien et al., 2016) and allowed for detection of specific target species (American bison, elks, fallow deer and grey wolf) in the presence of other wildlife (Chrétien et al., 2015). Like CNNs, there is also potential for OBIA approaches to be used to detect and classify multiple species simultaneously (Chrétien et al., 2015, 2016). Consistent with the findings of Abd-Elrahman et al. (2005) and Christiansen et al. (2014), spectral thresholding based on temperature, size and shape of pixel clusters was sufficient to accurately detect individual Grey seals that were consistent in these three attributes in a homogeneous environment that provided a large contrast to the seal pixels on these same attributes (Seymour et al., 2017).

Support-vector machine approaches were also used in two studies post-2015 (Table 2). These approaches involved supervised classification of image data into two categories, in one case distinguishing bird and non-bird objects in a simulated nesting colony of Greater Crested Tern on an open beach (Hodgson et al., 2018), and animal and non-animal objects in the African savannah (Rey et al., 2017). Support-vector machine methods resulted in a high probability of detection and low rates of misclassification in both studies; however, these approaches are limited to only two classes meaning they cannot distinguish between more than one class for wildlife and one class for the background environment (Hodgson et al., 2018; Rey et al., 2017). Therefore, specific species cannot be detected if there are other species present in the images being analysed (Hodgson et al., 2018; Rey et al., 2017). The accuracy of classification using support vector machines also depends on the two classification categories being as distinct as possible, with less accurate results likely to be found in surveys where the contrast between target wildlife and the background in terms of colour (for RGB imagery) or temperature (for infrared imagery) is low (Hodgson et al., 2018). Other objects present in images that are similar in colour or temperature are also likely to be incorrectly classified as the targeted wildlife (Hodgson et al., 2018; Rey et al., 2017).

Another novel method that was used in studies from 2015 was an approach referred to as the detection moving wild animals algorithm (DWA) which detects animals in images based on the difference in displacement of pixels of moving animals versus stationary background pixels between consecutive frames collected during drone flights (Oishi et al., 2018). This was found to accurately detect sika deer in a more complex environment than previous studies that attempted automated detection of terrestrial mammals but is limited in its application as it cannot be used to distinguish between species that move at a similar speed or to identify animals that remain stationary during surveys (Oishi et al., 2018).

Two studies published since 2015 utilised unsupervised pixel-based image classification approaches (Table 2), which differ from supervised pixel-based image classification in that instead of researchers manually tracing target objects in training images and assigning classes to them for the algorithm to use in classification, the computer determines these classes from training images on its own (Chrétien et al., 2016; Liu et al., 2015). The lack of manual input in training required to perform unsupervised pixel-based image classification means that it requires less time and effort from researchers, which is the main reason it was explored as an option for detection of wildlife in drone-derived imagery (Chrétien et al., 2016; Liu et al., 2015). However, while a high probability of detection was achieved using this approach for Black-faced spoonbills in a homogeneous environment without canopy cover or any other physical obstructions (Liu et al., 2015), it resulted in a low probability of detection for white-tailed deer in more heterogeneous environments with more complex vegetation (Chrétien et al., 2016).

The predominant automated detection method used in eight studies published since 2015 were convolutional neural networks (CNNs) (Table 2). In contrast to the simple binary or interval-based thresholds used in earlier spectral thresholding and template-matching approaches, CNNs classify objects based on a much higher level of detail (Chen & Liu, 2017; Halstead et al., 2018; Tang et al., 2017). The spectral value of each individual pixel and its proximity to other pixels in the matrix of the image is used to detect distinct ‘features’, such as the outline of a target animal's body shape (Chen & Liu, 2017; Halstead et al., 2018; Tang et al., 2017). CNNs are then able to classify particular target animals based on the similarity between the ‘features’ in testing and training images (Chen & Liu, 2017; Halstead et al., 2018; Tang et al., 2017).

This allowed for detection of wildlife in situations with more varied contrast between the animal and their background such as habitats with complex vegetation, and less consistency in size, shape, colour and temperature of target animals as this type of algorithm can recognise when an object in a test image matches most but not all of the expected ‘features’ and still classify the object correctly (Corcoran et al., 2019; Hong et al., 2019; Kellenberger et al., 2019; Longmore et al., 2017). CNNs can also identify multiple object classes in images, meaning there is potential to use these methods for multispecies detection (Corcoran et al., 2019; Hong et al., 2019; Kellenberger et al., 2019). Another reason CNNs have been used frequently in recent studies is that suitable training images for wildlife from the viewpoint of a drone, particularly in the infrared spectrum, are often scarce (Corcoran et al., 2019; Hong et al., 2019; Kellenberger et al., 2019; Longmore et al., 2017). Through a process referred to as ‘fine-tuning’, existing general purpose CNNs capable of detecting a wide range of objects can be re-trained with a relatively small training dataset to detect a specific target in a specific context, in this case a particular wildlife species in drone-acquired imagery (Chen & Liu, 2017; Halstead et al., 2018; Tang et al., 2017). All studies reviewed that used CNNs took advantage of the practicality and efficiency of fine-tuning pre-existing CNNs including Faster R-CNN, YOLO, and HOG detectors to identify their target species (Corcoran et al., 2019; Gorkin et al., 2020; Hamilton et al, 2020; Hong et al., 2019; Kellenberger, Marcos, Courty, et al., 2018; Kellenberger, Marcos, & Tuia, 2018; Kellenberger et al., 2017, 2019; Longmore et al., 2017). This meant that a corpus of only a few hundred images was required to train the CNN used for automated detection, rather than the hundreds of thousands of images usually required for other machine-learning-based methods (Chen & Liu, 2017; Halstead et al., 2018; Tang et al., 2017). This allowed for automated detection of species such as koalas and gemsboks that are more elusive than those studied prior to 2015, for which gathering a large corpus of training images would have been challenging (Corcoran et al., 2019; Kellenberger, Marcos, Courty, et al., 2018; Kellenberger, Marcos, & Tuia, 2018; Kellenberger et al., 2017, 2019) (Table 2).

3.5 | Summary and recommendations

In terms of survey design, studies of automated detection of wildlife in drone-acquired imagery conducted over the last 5 years indicate that the use of a fixed-wing platform and RGB sensor should be recommended for large species occurring over wide areas with little to no canopy cover, as animals are likely to be easily recognisable in images, and this approach is more efficient in terms of cost and battery life, and allows a larger area to be surveyed (Kellenberger, Marcos, Courty, et al., 2018; Kellenberger, Marcos, & Tuia, 2018; Kellenberger et al., 2017, 2019; Rey et al., 2017). While no studies explicitly state that infrared imagery would not work for shore birds, the performance of automated detection methods on RGB imagery suggests that infrared sensors are not necessary, as the contrast between the birds and their background is sufficient for successful identification, though use of a multirotor drone is recommended to achieve a high enough ground resolution to clearly view these smaller species (Afan et al., 2018; Hodgson et al., 2018; Hong et al., 2019; Liu et al., 2015; Rush et al., 2018).

For other small, more elusive species, or species occurring in more heterogeneous environments with more environmental features that could cause occlusion, flying with a multirotor drone with an infrared sensor during early morning hours when the temperature is lowest is recommended, as this type of drone allows for higher ground resolution and maximum contrast between the body temperature of the animal and their background (Chrétien et al., 2015, 2016; Corcoran et al., 2019; Longmore et al., 2017; Oishi et al., 2018).

Simple automated detection approaches such as spectral thresholding and supervised pixel-based image classification have been shown to be sufficient to accurately detect wildlife of a consistent size, shape, colour and temperature in homogeneous environments lacking complex vegetation or other objects that might obstruct animals from view or be misidentified as animals (Rush et al., 2018; Seymour et al., 2017). However, methods that classify objects based on more complex criteria have been shown to be necessary for accurately detecting species with more individual variation in appearance in more heterogeneous habitats with more complex vegetation structure (Afan et al., 2018; Chrétien et al., 2016; Corcoran et al., 2019; Kellenberger et al., 2019). Of the more complex machine-learning-based approaches used to detect wildlife in drone-acquired imagery over the last 5 years, CNNs offer the most potential advantages to ecologists. They have consistently been shown to yield accurate results, allow for the possibility of simultaneous multispecies detection, and the reduced effort required to train CNN algorithms through fine-tuning means they are more efficient than other methods that require collection and/or manual annotation of a large corpus of training imagery, and they can be used to survey species that are more cryptic and elusive than has previously been possible (Corcoran et al., 2019; Hong et al., 2019; Kellenberger, Marcos, Courty, et al., 2018; Kellenberger, Marcos, & Tuia, 2018; Kellenberger et al., 2017, 2019; Longmore et al., 2017).

Overall, technological advances in machine-learning-based automated detection methods, drone platforms and sensors have led to the successful detection of individual animals under a wider range of species in a wider range of environments than previously thought possible (Chabot & Francis, 2016; Hollings et al., 2018; Linchant et al., 2015). The explicit impacts of canopy cover and topography on automated detection remain largely unknown, although a few recent studies suggest it is feasible to overcome the challenges presented by more complex survey areas with the appropriate combination of drone platform, sensor and detection method (Corcoran et al., 2019; Oishi et al., 2018). There is also little known about how differences in platforms, sensors and design of drone wildlife surveys affect the number of false positives yielded by automated detection methods, as few studies to date have explicitly reported precision rates despite many stating misidentified objects were a challenge to producing accurate counts of the target species (Corcoran et al., 2019; Francis et al., 2020; Gorkin et al., 2020; Hong et al., 2019; Kellenberger, Marcos, Courty, et al., 2018; Kellenberger, Marcos, & Tuia, 2018; Kellenberger et al., 2017, 2019; Rey et al., 2017). Further studies should be carried out to investigate the effect of these variables on the probability of detection and precision rate for species of different sizes in both RGB and infrared imagery to better inform the selection of suitable sites for automated detection and counting of vulnerable wildlife species to provide insight for conservation managers (Anderson & Gaston, 2013; Burke et al., 2019; McCafferty et al., 2015; Renwick et al., 2011).

AUTHORS' CONTRIBUTIONS

G.H. led the team; E.C., M.W. and A.S. conducted the literature review. All authors contributed critically to the writing and review of the article, with the first draft written by E.C., M.W. and A.S. All authors gave final approval for publication.

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DATA AVAILABILITY STATEMENT

This study is a review and synthesis of previously published work and as such does not contain any data.

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