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Wildlife detection, counting and survey using satellite imagery: are we there yet?

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ABSTRACT

Wildlife surveys are key to assessing the health of global biodiversity. Traditional field and aerial methods however have significant limitations, including high costs, substantial time investment, and potentially biased estimates. The increasing availability of high-throughput monitoring sensors in recent years has opened new perspectives for wildlife studies. Very-high-resolution (VHR) satellite sensors promise large spatial and temporal coverage while seemingly being less costly than traditional methods. Deep learning (DL) has shown increasingly impressive capabilities for processing remote sensing imagery, suggesting good prospects for imagery-based wildlife surveys. We reviewed all taxa and geographic area studies that use satellite imagery for wildlife detection, counting and surveys. Through an analysis of 49 peer-reviewed papers, this study examined the sensors and resolutions employed along with the methods used to detect, count and survey wildlife in various biomes. Results have revealed an increasing trend of publications. Mammals and birds are the focus of most of the papers, mainly in polar/alpine and pelagic ocean waters biomes. Visual interpretation is the most common method used for wildlife detection and counting while total count is mostly used for surveying. Most of the papers present a proof of concept to detect, count and survey wildlife. Technological advances are expected to enhance the spatial and temporal resolutions of satellite imagery, as well as image processing capabilities. Three main bottlenecks preventing the development of on-demand operational approaches for wildlife surveys were identified: 1) the business model of VHR satellite imagery providers is not conducive to wildlife studies; 2) satellite imagery is rarely shared; and 3) the training of multidisciplinary highly qualified personnel is underdeveloped. In response, this review presents key research priorities for advancing remote sensing for wildlife monitoring. They include wildlife-dedicated satellite constellations at enhanced spatial and temporal resolutions, increased data accessibility and sharing, adapted survey strategy, development of foundational DL model and multidisciplinary integration. We believe that progress in these directions will foster new survey strategies that are certain to revolutionize wildlife monitoring in the decades to come.

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Wildlife; remote sensing; satellite imagery; survey; deep learning

1. Introduction and background

Biodiversity loss is one of the most significant environmental crises, threatening the survival of human civilization (Ceballos, Ehrlich, and Raven 2020). Wildlife surveys are key data for characterizing and monitoring biodiversity, but current tools and methods make it difficult to rapidly survey large areas and often provide potentially incomplete and biased estimates (Tuia et al. 2022; Turner 2014).

Most survey data are acquired using traditional field methods, which are costly and time-consuming, and present important limitations related to the accessibility of the territory and the areas covered (Davis et al. 2020; Seidlitz et al. 2021; Tuia et al. 2022). For several decades, aerial surveys have been used to survey species distributed over large areas, especially those that are not easily accessible or over rugged terrain (Davis et al. 2022; Krebs 2006). Aerial surveys are generally limited to direct visual detection (and occasional imagery) and are subject to biases associated with the subjectivity of human observation and observer disturbance, in addition to posing a significant risk of accidents (Schlossberg et al. 2016; Tuia et al. 2022). The main counting errors associated with aerial surveys are usually related to false negatives; observers often miss individuals, especially species in small groups (Lamprey et al. 2020). Although much work has been done to reduce

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these errors, the precision and accuracy of counts remain limited and impact the effectiveness of management actions for some populations and species (Brack et al. 2018; Davis et al. 2022).

Over the past few years, the increasing availability of numerous *in situ* sensors has opened new perspectives for wildlife surveys. Camera traps, geolocation tracking devices, drones, sound sensors, cellphones, and environmental DNA analysis are increasingly used as survey methods, creating unique opportunities for wildlife monitoring (Hughey et al. 2018; Lahoz-Monfort and Magrath 2021; Turner 2014; Whitford and Klimley 2019). However, despite this growing availability, these *in situ* devices still require intensive field effort for deployment (e.g. camera trap installation, access the territory to flight drones), have a low sampling rate, and require maintenance in varying conditions (e.g. cold, humidity, rain) that can affect their performance (Dyo et al. 2012; Newey et al. 2015). The use of these sensors can also impact the behavior of some species (Ditmer et al. 2015; Vas et al. 2015) or even their survival (Arnemo et al. 2006; LeTourneux et al. 2022). Moreover, the ratio of generated to useful data is very high and leads to a very high amount of data in multiple formats to manage and process (Lahoz-Monfort and Magrath 2021; Tuia et al. 2022).

Earth observation satellite sensors have provided images since the 1980s, with increasing spatial, temporal, and spectral resolutions. Following the advent of satellites capable of providing imagery at sub-meter resolutions (i.e. very high resolution, or VHR), several studies have focused on the use of this type of imagery for wildlife surveys, primarily to detect terrestrial and marine mammals (Hollings et al. 2018; D. Wang, Shao, and Yue 2019). Despite the tantalizing potential of these images thanks to their global terrestrial coverage, their potential for high acquisition frequency (e.g. daily) and the archiving of historical images, and their relatively low acquisition cost compared to field data acquisition, there are still limitations to wildlife detection. LaRue et al. (2017) identified 3 minimum necessary criteria for the detection of wildlife using VHR images: 1) an open landscape; 2) a sufficient body size to be detected or a positive indicator of the targeted species' presence; and 3) a contrasting color of the animal with the landscape. In addition, there are other limitations related to the availability of good quality images (e.g. cloud-free) at the targeted periods and for the targeted regions, as well as the high costs of some VHR images, especially over large territories (D. Wang, Shao, and Yue 2019).

In parallel with the development of sensors, the field of machine learning and especially deep learning (DL) has produced a stunning acceleration of massive data processing capabilities (LeCun, Bengio, and Hinton 2015). Specifically, in the field of imagery applied to Earth observation (Hoeser and Kuenzer 2020; Hoeser, Bachofer, and Kuenzer 2020; Zhao et al. 2019) and wildlife detection (Christin et al. 2019; Delplanque et al. 2022; Eikelboom et al. 2019; Kellenberger et al. 2021; Lee et al. 2021; Peng et al. 2020), approaches based on object detection using convolutional neural networks (CNNs) have the potential to automate the detection and counting of individuals with higher detection rates than conventional surveys, while significantly reducing costs and analysis time (Norouzzadeh et al. 2018; Tuia et al. 2022). Although these approaches have thus far been applied mainly on proximal (e.g. camera traps) and aerial (e.g. drones) imagery, their potential combined with the increasing availability of satellite imagery at very high spatial and temporal resolutions could represent a major advance in wildlife detection and survey techniques.

Several review papers on wildlife detection, counting or survey using remote sensing imagery have been published in the last decade (Butcher et al. 2021; Clarke et al. 2021; Corcoran et al. 2021; Delisle et al. 2023; Edney and Wood 2021; Goddijn-Murphy et al. 2021; Hollings et al. 2018; Jiménez López and Mulero-Pázmány 2019; Kuenzer et al. 2014; LaRue, Stapleton, and Anderson 2017; Linchant et al. 2015; Nazir and Kaleem 2021; Petrou, Manakos, and Stathaki 2015; Petso, Jamisola, and Mpoeleng 2021; Pettorelli et al. 2014; Sánchez-Díaz and Mata-Zayas 2019; Wang, Shao, and Yue 2019; Weinstein and Prugh 2018). However, none of them focused systematically and specifically on the use of satellite imagery, nor did any attempt to cover all taxa and geographic areas (Appendix A1). Moreover, a high number of papers have been published on these topics since the last systematic reviews were applied on papers from 2018 and earlier (40% of papers selected in the present review were published after 2018). Considering the very rapid evolution of image processing approaches combined with the increasing availability of satellite imagery at very high spatial, temporal, and spectral resolutions, a systematic and up-to-date literature review is needed.

The objectives of this paper are: (1) to provide a systematic review of existing studies that used satellite imagery to detect, count and survey animal populations; (2) to identify bottlenecks to efficient wildlife detection, counting and surveys using satellite imagery; and (3) to offer valuable perspectives and identify key research priorities for the next decade.

This review paper is organized into 5 main sections: (1) "Methods," in which we present our paper search strategy, selection criteria and definition of important terms; (2) "Results," in which we examine spatial and temporal publication trends, followed by an analysis of studied species, biomes and image processing methods; (3) "Discussion," in which we focus on and discuss sensors, resolutions, and methods employed for wildlife monitoring. It covers detection criteria, Ground Sampling Distance (GSD), spatial and temporal aspects, cost considerations and data sharing practices; (4) "Perspectives," in which we present the key research priorities identified, covering data resolution, accessibility, survey strategies, deep learning and multimodal integration; (5) "Summary and Conclusions," where we summarize and highlight the main bottlenecks and key priorities for advancing remote sensing for wildlife monitoring.

2. Methods

A comprehensive peer-reviewed paper search was performed using the Scopus database. Three concept combinations using boolean operators (AND between concepts and OR between synonyms) were defined as follows and used as keywords in the databases search: Concept 1: satellite, remote sensing, remotely sensed; Concept 2: wildlife, animal, bird, fish, mammal; Concept 3: counting, survey, detection. The preliminary list of papers was completed by reviewing the lists of references in each selected paper. The paper search was performed on works published up to September 2023.

A final selection was performed after applying the following six criteria, determined prior to the research: (1) only papers written in English were selected; (2) papers dealing with indirect counting were selected (e.g. wombat warrens, bird nests) when the objective of the study was to provide a direct relationship with population size; (3) reviews without a case study and non-peer-reviewed papers were excluded; (4) only papers focusing on non-microscopic and moving animals were selected (i.e. excluding groups of species such as corals and zooplankton); (5) papers focusing only on habitat or Global Navigation Satellite Systems (GNSS) localization of individuals were excluded; and (6) papers using only platforms other than satellite were excluded.

It is important to highlight that, for the context of this study, the terms detection, counting, and surveying have been dissociated and defined as follows:

Detection: The process of searching for and pinpointing individuals or groups of individuals belonging to a species within a satellite image. While the results may yield count values, this aspect is not performed systematically. Detection may be confined to the approximate location of a group of individuals or to a presence indicator.

Counting: The estimation of the number of individuals present within a predetermined portion of a satellite image or the entire image. If the counting method employed encompasses the entire area intended for surveying, counting may be deemed equivalent to surveying.

Surveying: The estimation of the population size of a species within the scope of its habitat or living area. Surveys may involve the utilization of spatial or temporal sampling techniques.

3. Results

The paper search and selection process yielded 49 peer-reviewed papers that employed satellite imagery for the purposes of wildlife detection, counting, or surveying (Appendix B). The results of the analysis are presented in the four following sections: 1) spatial and temporal trends observed in the selected publications; 2) studied species and biomes; 3) sensors and resolutions used; and, 4) methods used for detection, counting, and surveying.

3.1. Spatial and temporal publication trends

Most of the publications come from America (Figure 1), with 49% of the articles published. More precisely, 45% come from the United States of America (USA), followed by Europe (37%), with 22% from the United Kingdom (UK), Asia (10%), and Australia (4%).

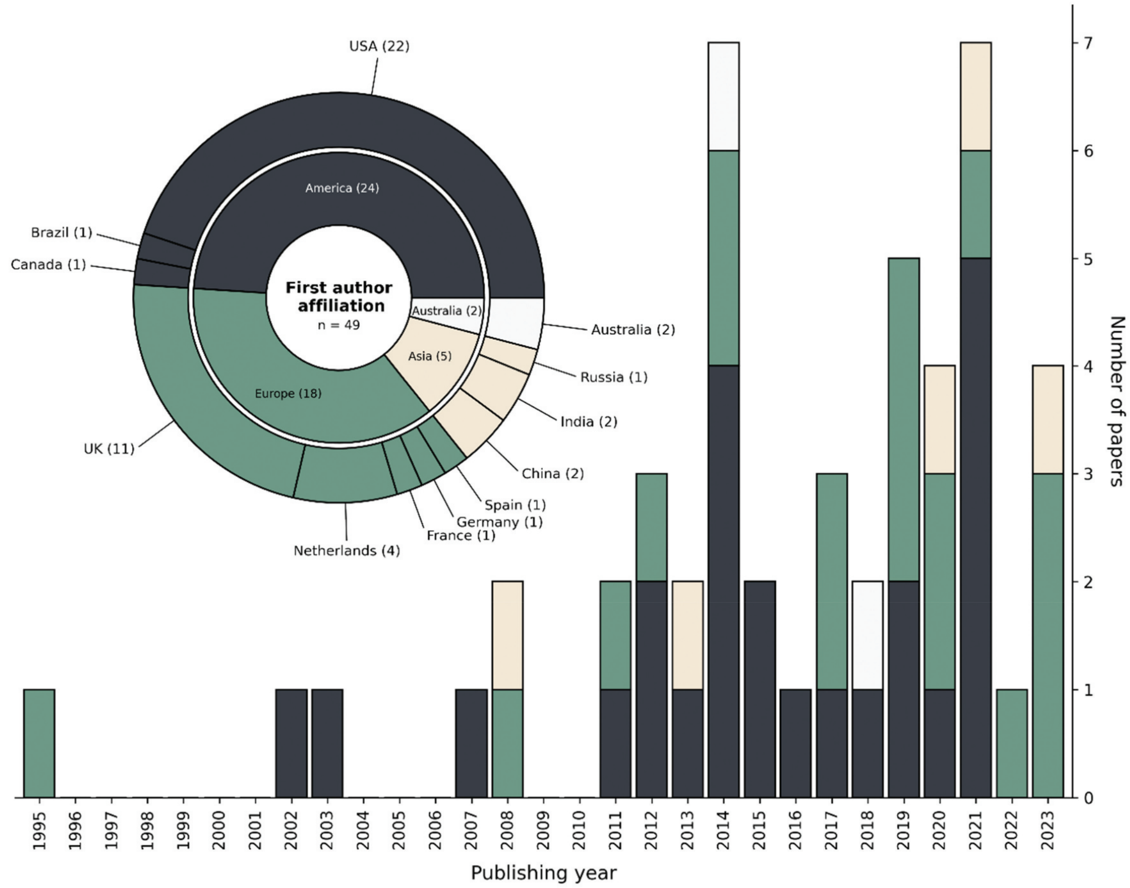


Figure 1. Historical trend of publications and overview of first author affiliation grouped by country and continent. Number of papers published are indicated in parentheses.

The temporal evolution of publications shows an increasing trend, the first being that of Guinet et al. published in 1995, in Europe. From 2011–2021, research works from America were published every year, while research from Europe was discontinuous (gaps of 1 and 2 years) before 2019, and then continuous until 2023. Australian and Asian teams published sporadically during this period. Two publication peaks occurred, in 2014 and 2021, both with 7 papers, dominated by American researchers. Only one paper was published in 2022.

3.2. Species and biomes studied

Among the 49 selected publications, two animal classes have been studied: the mammals class (Mammalia), studied in 33 papers; and the birds class (Aves), studied in 17 papers (Figure 2). More than 25 mammalian species were studied, spread into 11 families: right whales (Balaenidae), rorquals (Balaenopteridae), bovids (Bovidae), elephants (Elephantidae), equids (Equidae), hippopotamus (Hippopotamidae), monodontids (Monodontidae), earless seals (Phocidae), bears (Ursidae), squirrels (Sciuridae) and wombats (Vombatidae). Regarding birds, more than 13 species were studied, spread into 5 families: anatids (Anatidae), albatrosses (Diomedeidae), flamingos (Phoenicopteridae), penguins (Spheniscidae) and sulids (Sulidae). The papers of Guirado et al. (2019) and Kapoor et al. (2023), did not mention the species studied but only the order, which was cetaceans (Cetacea).

The species families most studied using satellite imagery were penguins (appearing in 24% of the papers), bovids (16%) and earless seals (12%), closely followed by rorquals (10%), bears and right whales (8% each). Penguins and earless seals have been mostly studied on the Antarctica coastline, making this continent the most studied to date (Figure 2). In fact, the polar/alpine (cryogenic) biome appeared in 37% of the papers, nearly equaled by the pelagic ocean waters biome (39%) which includes the sea ice functional group (Keith et al. 2022). Polar bears were studied in northern Canada and in the

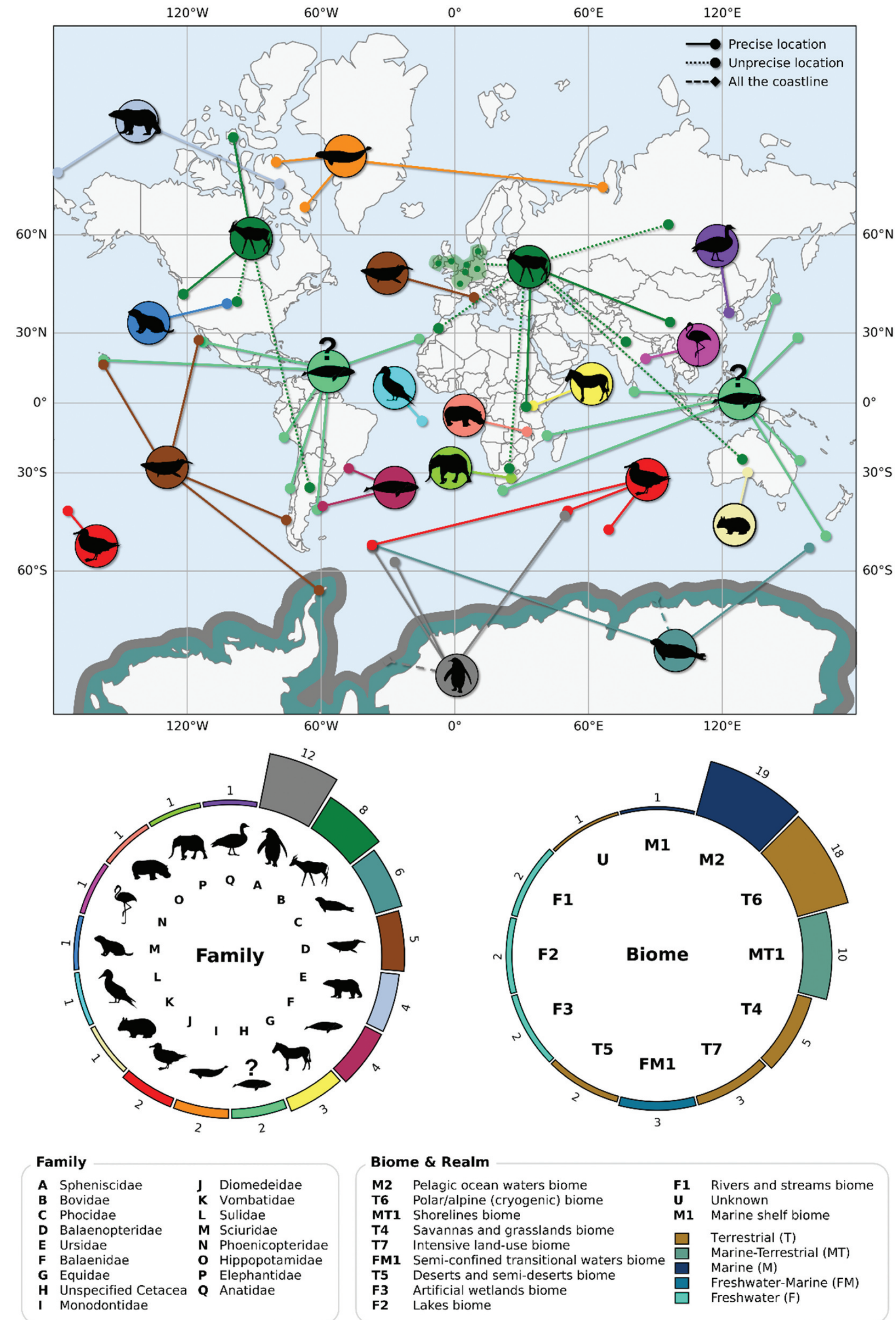


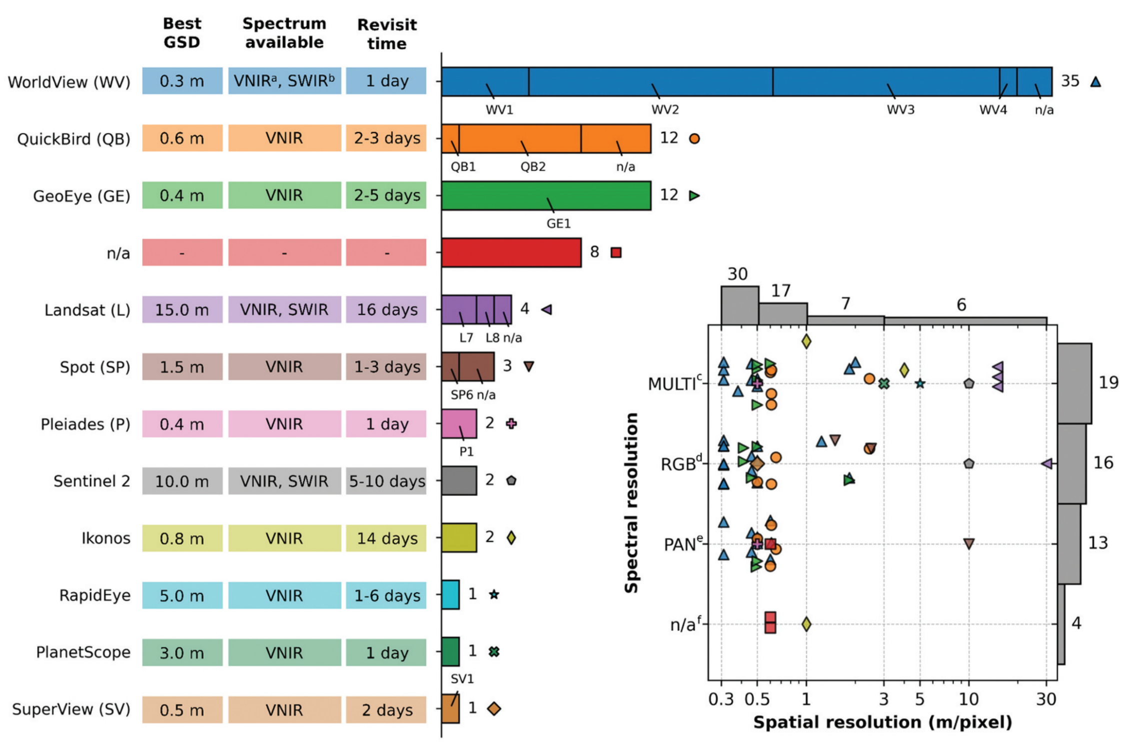
Figure 2. Spatial distribution and overview of the studied species and biomes. The location of study areas was determined using the information in the papers (i.e. geographical coordinates and/or use of the figures and places mentioned). The biomes were determined by selecting the most representative biome of each study area, using the IUCN global ecosystem typology (v2.1) maps (Keith et al. 2022). The numbers above each bar correspond to the number of published papers.

northwestern Russian Federation in these two biomes (Figure 2). The shorelines biome (20%) is linked to coastal species such as albatrosses, sulids, and certain cetacean species. Cetaceans (i.e. right whales, rorquals and monodontids) were mainly found in the marine realm, not far from coasts or islands around the world, while water birds (i.e. anatids and flamingos) were found in freshwater realms. Bovids, encompassing a wide range of terrestrial and aquatic biomes, were studied extensively due to their broad global distribution across diverse geographical regions (Figure 2).

It appeared that most of the papers (88%) focused on homogeneous and open habitats such as polar regions, waters, or shorelines leading to a generally acceptable contrast with the targeted species. Few papers studied heterogeneous landscapes (Duporge et al. 2021; Wu et al. 2023; Xue, Wang, and Skidmore 2017; Yang et al. 2014), likely due to the added complexity this poses for detection.

3.3. Sensors and resolutions

A total of 11 sensor types were employed for space-based animal detection (see Figure 3); the type used most frequently was WorldView (WV), used in 71% of the papers, followed by QuickBird (QB) and GeoEye (GE), each used in 24% of the papers. These three sensor types, alongside Pleiades (4%), possess a submeter resolution panchromatic band, which is often leveraged to enhance the resolution of other spectral bands through pan-sharpening techniques. Consequently, most of the papers examined animals at a very high resolution (<1 m/pixel), using multiple spectral bands (see Figure 3). Lower resolution sensors (>1 m/pixel) were commonly employed for detecting larger animals (e.g. cetaceans) or identifying presence indicators of specific species, for example penguin guano (Schwaller, Southwell, and Emmerson 2013), wombat warrens (Swinbourne et al. 2018) or prairie dog burrow mounds (Sidle



[a]visible and near-infrared (400 – 1100 nm); [b]short-wave infrared (1 – 2.5 µm); [c]multispectral, i.e. > 3 bands; [d]red, green and blue bands; [e]panchromatic; [f]not available

Figure 3. Overview of sensors used in the studies and the spatial and spectral resolutions of imagery used. The numbers next to or above each bar indicate the number of papers. 'n/a' means that the information was not available. Note that since some articles used several sensors with different spatial and/or spectral resolutions, the number indicated above the bars of the scatter plot does not necessarily correspond to the number of points.

et al. 2002). Finally, 8 papers (16%) did not specify the sensor used; instead, the authors mentioned the application employed to obtain satellite imagery (e.g. Google Earth), the commercial company from which the images were purchased (e.g. DigitalGlobe), or provided no information on this matter.

In terms of spectral resolution, multispectral (i.e. >3 spectral bands) images were used in 39% of the paper, followed by optical (i.e. red-green-blue bands) images (33%) and panchromatic (one-band) images (27%) (Figure 3). While most species appeared to be studied with optical and multispectral imagery, the spectral bands used rarely exceed red-green-blue and or red-green-blue and near-infrared. Beyond these bands, only Fretwell et al. (2014, 2019). have used a wider spectrum to detect whales, i.e. 9 bands including coastal bands.

Regarding the temporal aspect, close to three-quarters of the studies (76%) incorporated images from multiple dates, while single-date studies accounted for 24% of the total. Some researchers used multiple images to monitor populations over several months or years (12%), but only a few species have been monitored over time, such as Weddell seals (Ainley et al. 2015; LaRue et al. 2011), southern right whales (Corrêa et al. 2022), penguins (LaRue et al. 2014; Naveen et al. 2012) or wildebeests (Wu et al. 2023). Other authors also used multiple images to identify target species (8%) like polar bears (LaRue et al. 2015; Stapleton et al. 2014) or wildebeests and zebras (Wu et al. 2023; Xue, Wang, and Skidmore 2017) by distinguishing them using a reference image devoid of animals. However, multiple images were primarily used to allow the coverage of the entire study area (59% of the papers).

3.4. Methods used for detection, counting and surveying

The various methods used for animal detection, counting, and surveying using satellite imagery are listed and categorized by validation methods and main limitations identified by the authors in those papers (Table 1). It should be emphasized that the limits stated in Table 1 are only those put forward by the authors of the selected papers. As our aim in this section is to present the results of paper analysis, we have decided not to interpret limits that were not highlighted by the authors. All the studies performed detection, while 80% extended to counting and 45% to surveying. A total of 8 method categories were identified for detection, 5 for counting and 3 for surveying.

3.4.1. Detection

The main detection methods utilized by these studies were visual interpretation, used in 55% of the papers, supervised pixel classification (37%), supervised object detection (8%) and change detection (8%). It should be noted that authors of the selected papers mainly used change detection as a guide to facilitate manual interpretation (Stapleton et al. 2014; Wu et al. 2023; Xue, Wang, and Skidmore 2017). Only LaRue et al. (2015) have evaluated this approach as an automatic detection method. Visual interpretation seems to be a powerful method for detecting animals, especially small-sized ones (e.g. Bowler et al. 2020), but it requires experts. Such methods can only be properly validated under specific conditions, i.e. the exclusive presence of the species in a given and known location, as well as the availability of ground truth data. Supervised pixel classifiers or supervised object detection were either used for positive indicator detection (e.g. penguin guano stains, LaRue et al. 2014) or for direct animal detection (e.g. wildebeests, Wu et al. 2023). They are trained on labeled data to use spectral information from the satellite image to search for pixels or groups of pixels defining target objects (e.g. animals). In theory, a high spectral resolution provides a better discriminating power to detect specific objects, which is why pan-sharpening is commonly used to keep both spatial and spectral information. Detection methods were mostly validated using ground and/or aerial survey data or by testing them on independent imagery.

The main limitations of non-automated detection methods (i.e. visual interpretation and change detection) were the high time investment, the need for experienced interpreters and the need for reference images to distinguish animals from landscape features. Regarding automated methods, the main limitation trends were the confusion with landscape features, the difficulties in differentiating species, and the reliance on specific environmental conditions to achieve adequate performance. While multispectral instead of panchromatic imagery was recommended for better detection of wildlife (Barber-Meyer, Kooyman, and Ponganis 2007; LaRue et al. 2015), it

Table 1. Overview of methods used for detecting, counting and surveying wildlife on satellite imagery, and their description, validation methods and main limits as described in the 49 reviewed papers. Note that as visual interpretation was usually used to create ground truth, only papers using this method to produce detection, counting or survey results were considered.

Task	Method	N[a]	Description	Validation methods[b]	Main limitations[c]
Detection	Visual interpretation	27	Visual interpretation of images by one or more human interpreter(s), sometimes with the help of reference data, in order to locate animals within each image.	Comparison with ground/aerial survey data Comparison of interpretations from multiple observers	Time-consuming Requires experienced interpreters Difficulty in identifying/differentiating species Detectability relies on environmental conditions
	Supervised pixel classification	18	Assignment of each pixel to a class by a classifier, trained on a labeled dataset.	Cross-validation Manual verification Test on independent imagery	Less reliable than visual interpretation Confusion with landscape features Difficulty in identifying/differentiating species
	Supervised object detection	4	Detection, localization and classification of objects of interest (i.e. animal or group of animals) within an image by a detector, trained on a labeled dataset.	Test on independent imagery	Detectability performance relies on environmental conditions
	Change detection	4	Use of an image without animals as a reference to detect changes (i.e. potential animals) in the image of interest.	Comparison with ground/aerial survey data	Time-consuming manual review Availability of concurrent overlapping images
	Histogram thresholding	3	Selection of an optimal threshold to be applied on a histogram of pixel values to maximize the signal of animals.	Comparison with manual detection Comparison with ground survey data	Less reliable than visual interpretation for small groups Confusion with landscape features Difficulty in identifying/differentiating species Detectability relies on environmental conditions
	Supervised image classification	2	Assignment of a class to the image by a classifier, trained on a labeled dataset.	Cross-validation Test on independent imagery	Confusion with landscape features Difficulty in identifying/differentiating species Detectability relies on environmental conditions
	Unsupervised object detection	1	Detection, localization and classification of objects of interest (i.e. an animal or group of animals) within an image by a detector, trained on an unlabeled dataset.	Test on independent imagery	Confusion with landscape features Detectability relies on environmental conditions
	Unsupervised pixel classification	1	Assignment of each pixel to a class by a classifier, trained on an unlabeled dataset.	Test on independent imagery	Not mentioned in the paper.
Counting	Visual interpretation	18	Visual interpretation of images by one or more human interpreter(s), sometimes with the help of reference data, in order to locate and count animals within each image.	Comparison with ground/aerial survey data Comparison of interpretations from multiple observers	Time-consuming Requires experienced interpreters Difficulty in identifying/differentiating species Detectability relies on environmental conditions
	Detection method results	17	Use of the detection method results for counting, or at least as an aid to counting.	Validation method(s) of the corresponding detection approach (listed in the detection section).	Main limits of the corresponding detection approach (listed in the detection section).
	Regression model	10	Use of a regression model to predict estimated counts from pixels occupied by animals and ground/aerial counts.	Cross-validation Comparison with population data from previous study(ies)	Relies on precise ground truth estimates Requires concurrent ground truth data Species interactions not considered
	Density extrapolation	2	Multiplication of a known density value by a surface area to obtain an estimated count.	Not mentioned in the papers.	Requires a precise known density value
	Pixel brightness value based	1	Use of a counting model based on pixel brightness and the probability of pixel occupancy by an animal.	Comparison with ground counts	Not mentioned in the paper.

(*Continued*)

Table 1. (Continued).

Task	Method	N[a]	Description	Validation methods[b]	Main limitations[c]
Surveying	Total count	19	The entire targeted study area is surveyed.	Comparison with other survey estimates Comparison with previous estimates Use of Monte Carlo procedure	Difficulty to estimate the availability bias for aquatic animals (i.e. the ratio of submerged individuals) Difficulty to estimate the natural variability of the population Risk of overestimation due to the persistence of presence indicator Inconsistency of the imagery acquisition time with the peak activity of the target species
	Sample count	5	Part(s) of the study area is(are) surveyed and the results are then used to obtain estimates for the entire area.	Comparison with ground survey estimates Comparison with estimates from total count approach	Difficulty to guarantee the representativity of the sample
	Mark and recapture	1	Usage of each observer's detections as an independent sampling period to generate capture histories, and eventually population estimates.	Comparison with aerial survey estimates	Absolute confirmation of presumed animals is impossible

[a]Number of papers that used the associated method; [b]Validation methods used in the papers; [c]Main limitations observed by the authors of papers.

has been shown that supervised pixel classifiers struggled to differentiate animals in habitat with similar spectral signatures (Barber-Meyer, Kooyman, and Ponganis 2007; Cubaynes et al. 2019; Fretwell et al. 2019; Yang et al. 2014), were temporally inconsistent (Fretwell et al. 2014; Labrousse et al. 2022) and were prone to produce a high number of false positives (Fretwell et al. 2014, 2019; Lynch, Schwaller, and Schumann 2014). These considerations may also be valid for the histogram thresholding method, as LaRue et al. (2015) and Laliberte and Ripple (2003) observed that the surrounding landscape of terrestrial animals (polar bears and cattle, respectively) showed similar reflectance values to their bodies. Nevertheless, Fretwell et al. (2014) showed that thresholding the coastal band (400–450 nm) was the best approach to detect whales compared to unsupervised pixel classification methods. To overcome this animal-landscape spectrum similarity concern, image differencing (i.e. change detection), in which values of a reference image are subtracted from values of a target image, could be the solution. However, this method requires two orthorectified overlapping images taken at relatively close time intervals. It has thus far been shown to be effective for automatically detecting polar bears on relatively flat and open terrain (LaRue et al. 2015).

The use of deep learning is very recent, with the first paper published in 2019, and is therefore still in its infancy. To date, 10 peer-reviewed papers have applied deep learning to detect wildlife from satellite imagery, with the target species being: cetaceans (Borowicz et al. 2019; Green et al. 2023; Guirado et al. 2019; Kapoor, Kumar, and Kaushal 2023), albatrosses (Bowler et al. 2020), cattle (Mücher et al. 2022), African elephants (Duporge et al. 2021), wildebeests (Wu et al. 2023), seals (Gonçalves, Spitzbart, and Lynch 2020), and penguins (Le et al. 2022). Borowicz et al. (2019) trained a CNN-based image classifier, ResNet-152 (He et al. 2016), on down-scaled aerial image patches to discriminate the presence of whales in satellite tiles. Related to this idea, Guirado et al. (2019) trained a CNN-based image classifier, Inception-v3 (Szegedy et al. 2016), to discriminate whales from water, submerged rocks and ships, and then added a second step to locate and count individuals in the resulting tiles using Faster- R-CNN (Region-based CNN), a CNN-based object detector (Ren et al. 2017). This object detector was also used by Duporge et al. (2021) to directly detect and count African elephants on VHR satellite images. Kapoor et al. (2023) used another object detector called "Tiny YOLO (You-Only-Look-Once) v3" (Redmon and Farhadi 2018) to detect cattle and Green et al. (2023 used YOLO v5 (Jocher, Stoken, and Borovec 2021) to detect gray whales. Other works used the U-Net architecture (Ronneberger, Fischer, and Brox 2015) to detect albatrosses (Bowler et al. 2020) and wildebeests (Wu et al. 2023), or an adapted version of it to detect and count pack-ice seals (SealNet, Gonçalves, Spitzbart, and Lynch 2020) or to segment penguin colonies (PenguinNet, Le et al. 2022).

3.4.2. Counting

The most common counting methods were visual interpretation, used in 46% of papers conducting counts, the use of detection method results to estimate counts (44%) and the use of regression models (26%) generally fitted to reliable ground truth estimates. Except for the use of detection method results, counting methods were usually validated by comparing their results to ground and/or aerial counts, or to previous population data. The primary limitations of counting methods were analogous to those of detection methods. The need for precise, reliable and concurrent ground truth estimates was critical for the success of regression and extrapolation methods.

3.4.3. Surveying

Finally, total counting, which accounted for 86% of the papers conducting surveys, sample counting (23%) and mark and recapture (5%) were the three methods used for surveying. Sample counting relies on the use of sample units selected over the census area. For instance, LaRue and Stapleton (2018) used full non-overlapping satellite images and LaRue et al. (2015) used plots selected from non-overlapping satellite images. The latter assessed the sampling requirements and investigated the effect of sample plot size on polar bear population estimates on Rowley Island. Their findings suggested that sampling 50% of the study area could strike a balance between reliable results and the associated cost of using VHR satellite imagery. They also observed that plot size did not significantly impact the reliability of the results. Mark and recapture was only used by Stapleton et al. (2014) who used the counting results of two independent interpreters and treated each result as an independent sampling period to generate capture histories for mark-recapture analysis. The abundance estimate they obtained was like the one derived from aerial surveys conducted at nearby dates.

The results of survey methods were typically validated by comparing them with other estimates or with previous estimates. Survey methods were primarily constrained by the challenge of estimating population parameters, including factors such as availability and variability, as well as ensuring the representativeness of the sample.

4. Discussion

4.1. Detection criteria

The relevance of using satellite imagery for wildlife monitoring or survey directly stems from the feasibility of detecting the target species in its surrounding habitat. To evaluate the feasibility of satellite imagery for wildlife studies, LaRue et al. (2017) established a set of eight detection criteria, categorized as primary or secondary. The primary criteria encompass three essential conditions that must be satisfied by a prospective system: 1) the presence of an open landscape; 2) a discernible color contrast between the target species and the surrounding environment; and 3) a target species possessing a detectable size or displaying positive indications of its presence. According to the authors, secondary criteria serve to enhance the utility of satellite imagery: 4) species-landscape differentiation, which entails a significant distinction between the target species' visual appearance and the surrounding landscape; 5) habitat associations, indicating the consistent presence of the species at specific locations; 6) temporal exclusivity, wherein the target species exclusively occupies an area during a specific time period; 7) coloniality, referring to the congregation of the target species in herds or groups; and 8) ground truthing, which involves the availability of accurate population data or ground validation for the detected species.

We observed that most of the selected papers reached primary criteria, while they varied among species and study areas for secondary criteria. Studies involving birds, whales or seals generally fulfilled all the criteria, while studies involving large terrestrial mammals (e.g. elephants, wildebeests) appeared to reach fewer secondary criteria, due mostly to poor temporal exclusivity, poor habitat associations and/or no ground truthing. Our trend results for the biomes studied revealed that most papers focused on homogeneous and open habitats. Recent studies have however demonstrated noteworthy levels of accuracy (approximately 80%) in detecting terrestrial mammals within heterogeneous landscapes using DL models (Duporge et al. 2021; Wu et al. 2023). Their results highlight the potential to overcome previous limitations related to heterogeneity and emphasize that continued advances in DL may further improve detection in diverse landscapes. In contrast, certain studies that satisfied most of the criteria exhibited inferior detection results because of heterogeneous coloration of animals (Fretwell et al. 2019), lack of animal-landscape differentiation (LaRue, Stapleton, and Anderson 2017), or many confusing landscape elements produced by other species or vegetation (Lynch, Schwaller, and Schumann 2014 This could be addressed using improved detection methods. These criteria are indeed predicated upon a human-centric detection paradigm, disregarding the potential processing capabilities of a computer that can effectively analyze and extract information from more extensive spatial and spectral data. Therefore, we propose that complementary characteristics, related primarily to satellite images processing and acquisition, need to be considered and are therefore addressed in the following sections.

4.2. Ground sampling distance

At spectral level, the main criterion for proper animal detection is a sufficient contrast between the target species and its surrounding landscape. At spatial level, GSD can be considered as the most critical criterion to detect animals as it is directly related to the level of details provided in imagery. Nevertheless, satellite design must deal with multiple trade-offs between spatial resolution and data volume, spectral resolution, and noise (Al-Wassai and Kalyankar 2013). Since the 2010s, there have been significant advances in spatial resolution with the launch of Worldview-1, which provides 50 cm resolution in the panchromatic band, and subsequently WV-4, which provides 30 cm resolution (Khan et al. 2023). As illustrated in Figure 4, a decimetric GSD is critical for the identification of medium-size species or individuals, particularly in high-density contexts. Several pixels are necessary to identify an animal on imagery, nine to ten pixels

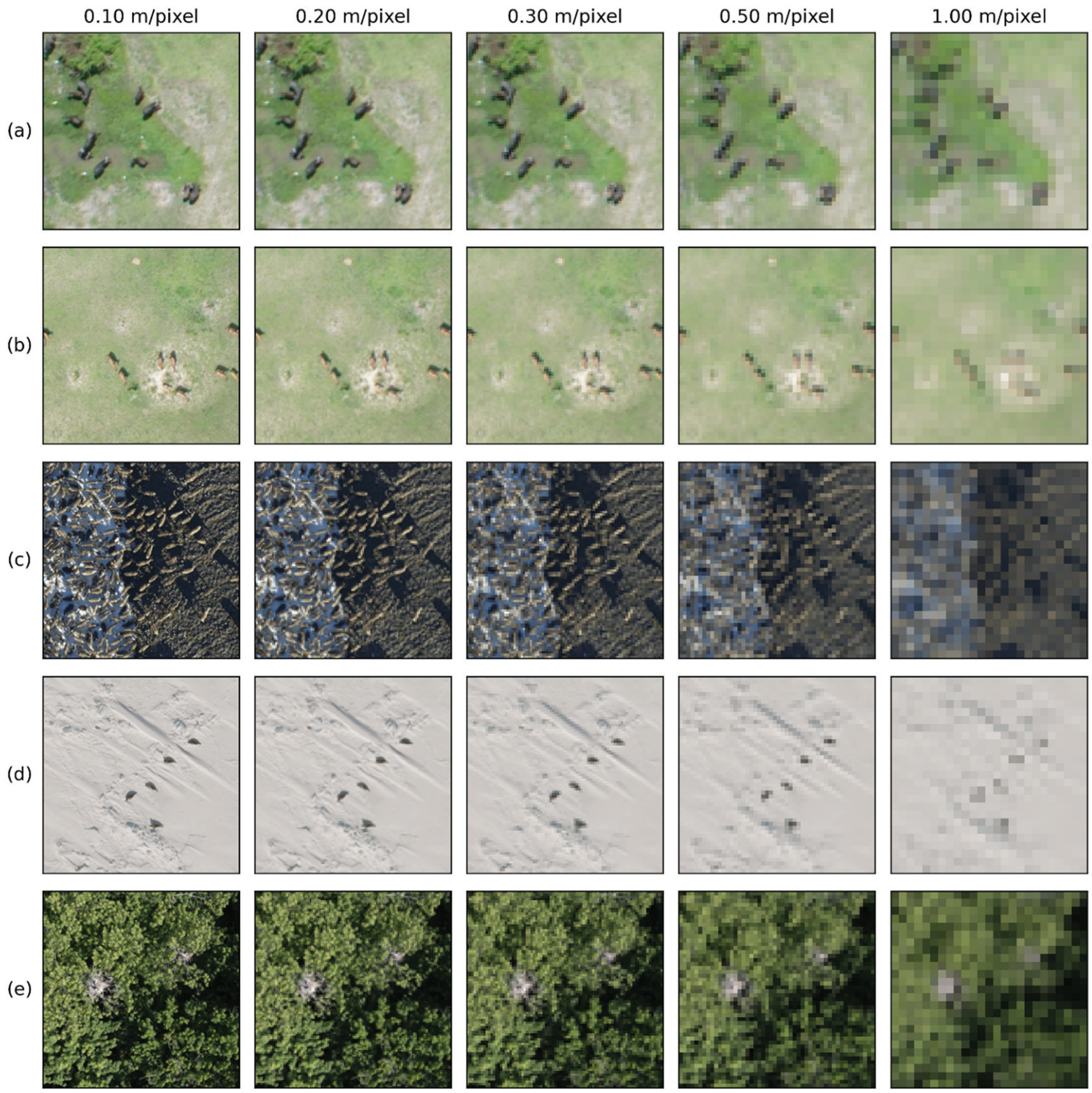


Figure 4. Spatial representation of multiple wildlife species under varying environments and ground sampling distances, simulating various satellite spatial resolutions and their impact on image clarity, species identification and high-density individual distinction: (a) African buffalo (*syncerus caffer*), (b) topi (*damaliscus lunatus jimela*), (c) caribou (*Rangifer tarandus*), (d) harp seal (*pagophilus groenlandicus*), and (e) nests of great blue heron (*Ardea Herodias*). Note that ultra-high resolution aerial images (< 5cm) were artificially down-sampled to simulate these different satellite resolutions. Images of African buffalo and topi (a, b) are samples from the dataset of Delplanque et al. (2022) with permission of the authors. Images of caribou, harp seal and great blue heron were shared by the Alaska Department of Fish and Game (c), fisheries and oceans Canada-québec (d), and the government of Quebec and CERFO (e).

being previously identified as a minimum size for detectability on visible (Wu et al. 2023) and thermal imagery (Burke et al. 2019). Considering that the highest resolution available is 30 cm/pixel, only large animals are directly detectable (e.g. whales, elephants), smaller ones being detectable using indicators of presence (e.g. guano, warrens), as shown in the reviewed papers (Figure 5). Small (i.e. under nine to ten pixels) animals also appear to be detectable, but this relies on prior knowledge of the species location, its surrounding habitat and its temporal behavior. For example, albatrosses have been detected and counted by insider personnel during their nesting period (Bowler et al. 2020), but would only appear as white spots on satellite imagery to inexperienced personnel (Figure 5a).

In addition, even if a species is detectable, differentiation between species of the same size seems difficult, if not impossible (Bamford et al. 2020; Wu et al. 2023; Yang et al. 2014). Fine-scale features (i.e. similar size of the target species) such as individual trees, small water bodies, or vegetation structure may

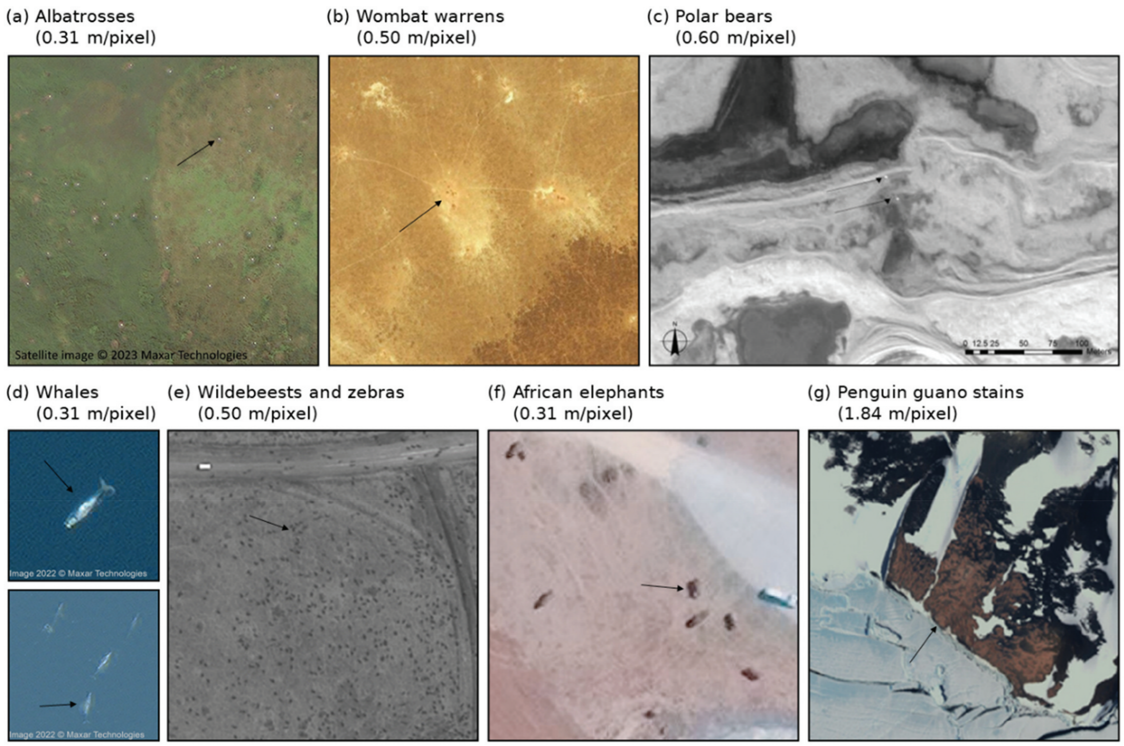


Figure 5. Examples of species studied using VHR satellite imagery: (a) Albatrosses (*diomedea Exulans*). Image from Bowler et al. (2020), printed with permission from the authors, copyright (2023), maxar technologies. (b) Wombat (*lasiorhinus latifrons*) warrens. Figure reprinted from Swinbourne et al. (2018), copyright (2018), with permission from Elsevier. (c) Polar bears (*Ursus maritimus*). Figure reprinted from LaRue et al. (2015), copyright (2015), with permission from John Wiley and sons. (d) Right whale (*Eubalaena australis*) and gray whales (*Eschrichtius robustus*). Images from Cubaynes et al. (2019), printed with permission from the authors, copyright (2022), maxar technologies. (e) Wildebeests (*connochaetes taurinus*) and zebras (*equus quagga*). Figure reprinted from Xue et al. (2017), copyright (2017), maxar technologies. (f) African elephants (*Loxodonta africana*). Figure from Duporge et al. (2021), copyright (2021), maxar technologies. (g) Penguin guano stains. Figure reprinted from Le et al. (2022), copyright (2021), with permission from John Wiley and sons.

also be difficult to discern (Fretwell et al. 2014; Irvine et al. 2019; Laliberte and Ripple 2003; McMahon et al. 2014; Xue, Wang, and Skidmore 2017), limiting the accurate assessment of population distributions. Multispectral imagery may nevertheless be helpful to distinguish species from confusing background features, or even among other species (Lynch et al. 2012). The lack of spatial resolution can impede the detection and monitoring of cryptic or elusive species that rely on camouflage or occupy densely vegetated and obstructed environments. Finally, the inability to discriminate between closely spaced individuals (Corrêa et al. 2022; Fretwell et al. 2019; Xue, Wang, and Skidmore 2017), between adults and calves (Cubaynes et al. 2019; Stapleton et al. 2014), and/or the persistence of presence indicators (Hughes, Martin, and Reynolds 2011) may also hinder the estimation of population densities and demographic parameters.

4.3. Spatial coverage

Satellite imagery covers relatively large areas compared to other types of imagery (e.g. aerial), allowing the acquisition of snapshots over very large territories. This enables animals to be counted at several spatial scales, ranging from a few tens of square kilometers to cover local areas (e.g. Bowler et al. 2020) to several thousand to cover vast territories (e.g. Cubaynes et al. 2019; Wu et al. 2023). Available VHR imagery can cover swath widths between 12 to 20 km (Khan et al. 2023), which can provide data not only on animals but also on their habitats. In these cases, although panchromatic bands can provide some radiometric and textural information, the additional use of multispectral bands (higher GSD) in visible and near-infrared domains is usually required for characterizing habitats or background (Goddijn-Murphy et al. 2021; Wang, Shao, and Yue 2019).

The spatial coverage of satellite images also gives access to any location on Earth, removing all limitations linked to the accessibility or dangerousness of a study area. This type of imagery also causes no disturbance to wildlife, and considerably reduces the deployment of field logistics. These characteristics are widely exploited in existing studies, as the vast majority of published articles focus on environments that have very low (polar/alpine (cryogenic) biome: 37%) or low (pelagic ocean water biome: 39%, shoreline biome: 20%) accessibility.

These spatial characteristics also limit certain survey biases. Wide territorial coverage means that a larger sample of a population can be surveyed compared to traditional methods, theoretically providing more accurate estimates (LaRue et al. 2015). This coverage, combined with the absence of disturbance, also limits certain detection biases linked to animal movement (e.g. double counting between flight transects). In the case of aggregating species (e.g. migratory ungulates, penguin colonies), satellite imagery opens opportunities for total count (e.g. Bamford et al. 2020; Labrousse et al. 2022, Wang et al. 2020; Wu et al. 2023). The latter would greatly increase the accuracy of population abundance estimations, currently limited by statistical constraints associated with the sampling of this type of heterogeneous and autocorrelated spatial distribution (Wu et al. 2023).

4.4. Temporal resolution

The revisit rate of the nine satellite sensors offering very high spatial resolution images currently ranges from less than 3 days to 2 times a day (Khan et al. 2023). This frequency therefore provides more than daily theoretical coverage of the Earth's surface and allows specific periods to be targeted with great precision. As wildlife surveys are often carried out during specific periods of the annual population cycle like open water season for whales (e.g. Charry et al. 2021), African ungulate migrations (e.g. Wu et al. 2023), seal breeding (e.g. Ainley et al. 2015), albatross nesting (e.g. Bowler et al. 2020), or flamingo wintering (e.g. Sasamal et al. 2008), a high revisit rate favors the availability of imagery in these time slots. Although most papers use satellite imagery at specific points in time to detect individuals or populations, some (LaRue et al. 2015; Stapleton et al. 2014; Wu et al. 2023; Xue, Wang, and Skidmore 2017) exploit this revisit rate in the detection approach itself by analyzing the temporal changes to identify individuals (i.e. moving targets) and to eliminate static confusing objects.

The continuous coverage of a territory over time also makes it possible to monitor populations over time at a relatively high frequency compared to traditional methods involving field logistics (Ainley et al. 2015, Corrêa et al. 2022; LaRue et al. 2011, 2014; Naveen et al. 2012; Wu et al. 2023). Without completely replacing traditional surveys, satellite imagery could increase their frequency while providing better reproducibility related to the objective nature of the information contained in the images and the use of automatic detection approaches. The use of traditional census approaches would remain important to validate the results obtained by image processing but could be carried out less frequently and over reduced areas (Wu et al. 2023).

However, these revisit rates remain theoretical, and several factors can influence the availability of images. For example, the shorter the targeted acquisition period, the lower the availability of imagery. As for traditional ground or aerial survey, weather conditions (e.g. sea state, cloud cover) may limit data collection during critical periods by disturbing or obscuring satellite views (Bamford et al. 2020; LaRue and Stapleton 2018; LaRue et al. 2011; Lynch et al. 2012). Finally, mosaics of scenes acquired at different dates are not adapted to wildlife surveys since wildlife is mobile.

4.5. Cost and availability of imagery

Although large web-based processing platforms such as Google Earth Engine and Microsoft Planetary Computer have democratized advanced image processing, the availability of VHR imagery remains very restricted and strongly limits the availability of images and their use for wildlife surveys. The cost of VHR satellite imagery may be a major obstacle to wildlife studies. Satellite imagery pricing varies according to several factors such as the image provider, type of demand (e.g. archiving, tasking, priority tasking), image resolution and spectral characteristics, level of processing, coverage area, licensing terms, and intended use. While it is difficult to give a precise estimate, as they are often linked to requests for quotations, prices can range from several hundreds to thousands of dollars per minimum-size ordered scene (25 to 100 km^2), resulting in prohibitive costs for covering large areas (Apollo Mapping 2023; LAND INFO Worldwide Mapping, LLC 2023).

Current sale conditions of satellite images also significantly limit their application to wildlife surveys. Large animals, the type most targeted by satellite imagery, generally occupy large and sparsely inhabited territories in low density, and their spatial distribution varies over time while being relatively unpredictable. The availability of images must therefore respond to these constraints by covering large territories, considering that most of them do not contain animals, and by acquiring images at specific times, often determined with very short advance notice. Although less expensive than tasked images, the availability of archived images is limited because satellites usually acquire imagery only when tasked by customers. Archive catalogs do not allow for a full resolution preview which makes it impossible to evaluate the presence of animals before purchase. Archived imagery is therefore of limited interest if specific periods and sites are targeted. On the other hand, tasking imagery also has several limitations such as: high prices, a low level of priority which does not guarantee their acquisition (highest priority being given to military and commercial applications), an acquisition window of several weeks (with no control on a specific acquisition date), and a limit on coverage areas and acquisition periods.

However, these acquisition constraints are not raised in the reviewed papers. Most of them presented a proof of concept regarding species detection or population estimation using satellite imagery that requires relatively few constraints on image acquisition, given that the study usually covered a relatively small area and the site and target period can be flexible. The few articles (Ainley et al. 2015; Fretwell et al. 2012; LaRue et al. 2011; Lynch and LaRue 2014; Wu et al. 2023) that carried out operational studies (i.e. total count, temporal monitoring) focused on fixed and known study areas (e.g. Antarctic nesting sites, wildlife corridors) associated with relatively large observation windows, which favor image availability. These acquisition constraints thus remain underestimated in the literature but represent a major obstacle to the development of future operational survey tools.

4.6. Image processing

Reducing the tedious and costly workload associated with the manual interpretation of satellite imagery is a high-priority achievement that would enable larger-scale wildlife monitoring, more frequent surveys and consequently more robust population estimates (Cubaynes et al. 2019; Fretwell et al. 2014, 2019; LaRue et al. 2015). Hence, various (semi-)automated detection and counting methods have been applied on satellite imagery containing wildlife, often providing promising results, but with limitations. Several authors suggest that object-based detection methods might be more appropriate to detect and count wildlife on satellite imagery because such methods use a combination of shape, texture and spectral characteristics to detect objects (Cubaynes et al. 2019; Fretwell et al. 2019; LaRue et al. 2015; Yang et al. 2014). In recent years, these characteristics have proven to be automatically and particularly well-leveraged by CNNs, a type of artificial neural network used in various DL approaches that has demonstrated great success in the detection of objects in images (LeCun, Bengio, and Hinton 2015). While earlier object detection methods, i.e. not using DL, struggled with detecting small-sized objects, recent advances in DL have shown increasing promise for small object detection tasks (Tong, Wu, and Zhou 2020). Objects occupying just a few pixels, like animals on remote sensing imagery, may be then detected by such DL methods (e.g. Delplanque et al. 2023; Sarwar et al. 2021). DL is undoubtedly the future for all image processing tasks and would leverage the massive amount of remote sensing data, but it is still in its infancy for satellite-based wildlife monitoring. Expert-based visual interpretation may nevertheless still provide value for detecting species against complex landscapes containing numbers of confusing elements. In such cases, a hybrid approach combining DL and human experts should be more effective. DL might handle scalability by directing human attention to areas of interest and experts might verify DL model predictions and provide additional training data. The expertise of visual analysts will thus likely continue playing a role even as automated image processing techniques progress.

As described in section 3.4, different DL approaches have already been considered for the detection and counting of animals in satellite imagery, each with promising and sometimes stunning results. Training supervised deep learning models starting from random weights requires however a large amount of labeled data, which is not easy to produce for wildlife. As an example, a common dataset used for everyday object detection is Microsoft Common Object in Context (COCO), a large-scale dataset containing more than 200,000 labeled images with 1.5 million object instances (Lin et al. 2014). Unfortunately, the size of the datasets we usually encounter is much smaller because of the significant cost and time involved for labeling. For this reason, in most surveyed papers, deep learning object detectors are typically derived from pre-trained backbones built on large computer vision training sets such as ImageNet (Deng et al. 2009). While this is a reasonable approach when training data are limited, there is evidence that spatial resolution and data preprocessing are not always appropriate for satellite imagery (Corley et al. 2023). This technique is commonly called "fine-tuning" and is widely used in various research domains. Nonetheless, one might ask how many samples are needed for the proper detection of wildlife in satellite images. This is not an obvious question, but the literature suggests some answers. Shahinfar et al. (2020) studied the effect of training sample size on the accurate classification of wildlife by CNNs in camera trap imagery. They observed that 150–500 images per class is sufficient to achieve reasonable performance when using fine-tuning. Even if it is somewhat similar, image classification differs from object detection, and we may still wonder about the minimum number of samples and annotated objects to perform satisfactory detection. Future research should clarify this aspect, but results of previous studies using deep learning for wildlife detection on satellite imagery still provide some indications. As an example, Guirado et al. (2019) reached a detection performance of 81% by using fine-tuning and 700 training samples per class, containing 945 animals. Similarly, Duporge et al. (2021) used only 188 training satellite tiles containing 1,125 animals and achieved an overall detection performance of 75% for both homogeneous and heterogeneous landscapes. Therefore, it seems that a few hundred training samples and around 1000 animal objects per class would be sufficient for the acceptable detection of wildlife by deep learning and satellite imagery.

4.7. Data sharing and multidisciplinarity

Sharing satellite imagery and annotations would certainly promote the development of automated or semi-automated detection models. Unfortunately, satellite images are often licensed by the selling companies (e.g. DigitalGlobe), which severely limits data sharing. In fact, among the 16 papers that announced the availability of their data, more than half gave the product identifier to purchase the image in the vendor's catalog, and only Yang et al. (2014) made the image used in their study freely available. As for the availability of the code for processing the satellite images, only 6 of the 49 reviewed papers made it freely available. However, as these 6 are recent (after 2018), we can hope that this will become a common practice.

In addition to data sharing, the collaboration between remote sensing and ecology communities remains an obstacle to the development of wildlife remote sensing, which mobilizes multidisciplinary expertise. For a long time, these communities evolved in silos, creating collaborative challenges linked to semantic gaps, reference frame gaps, as well as differences in needs and constraints regarding data and targeted results (Kuenzer et al. 2014; Pettorelli et al. 2014). As an indication, the first publications combining the keywords "remote sensing" and "biodiversity" date back to the early 1990s, and only 65 articles were published between 1990 and 2000 (compared to more than 200 every year recently) (Wang and Gamon 2019). This period also corresponds to the first articles on remote sensing of wildlife using satellite imagery. The recent advent of Earth observation big data combined with the development of processing approaches based on machine learning has propelled these disciplines toward each other, opening new perspectives for wildlife characterization at different spatio-temporal scales (Tuia et al. 2022).

5. Perspectives

Based on the research projects made in the last decades, we believe that future developments of wildlife detection and survey using satellite imagery will be related to developments in 6 main axes: 1) spatial and temporal resolutions; 2) image accessibility and availability; 3) survey strategy; 4) deep learning and multimodal integration; 5) data and code sharing; and 6) training and multidisciplinarity.

5.1. *Spatial and temporal resolution of images*

Given that GSD is a determining factor in the detectability of animals on satellite images, the future availability of imagery at resolutions of less than 30 cm is a key factor in the widespread use of this type of data. We therefore believe that the future direction of research and technology should be toward low cost solutions such as Lower Earth Orbits (LEOs) satellites, High-Altitude Pseudo-Satellites (HAPS) or High Altitude and Long Endurance (HALE) drones. Missions such as Albedo[1] are currently underway to acquire imagery at a GSD of 10 cm (visible) and 2 m (thermal) using LEO satellite. At the same time, microsatellite technology for Very Low Earth orbits (VLEOs) between 250 and 500 km is quickly advancing. The deployment of constellations of dozens of small, low-cost satellites, each less than a meter in diameter will potentially improve the radiometric performance of optical, LIDAR and radar instruments as well as the temporal coverage. The number of constellations of micro and small satellites has greatly increased with nearly 1,000 spacecrafts in orbit forecasted for 2022 (Curzi, Modenini, and Tortora 2020). These constellations, with their high revisit rate – multiple times daily – will enable more accurate, comprehensive and timely mapping, providing a clearer understanding of conditions on the ground. Decimetric spatial resolutions could be envisioned at the cost of smaller swath widths, therefore requiring more revisiting orbits to cover a targeted area. As these spacecrafts are deployed in greater numbers and in less-traditional circular orbits, constellations can be formed that can offer more frequent revisit opportunities and thus improved temporal resolution. However, atmospheric drag will significantly reduce the sensor lifespan, which can impact data continuity.

As for HAPS and HALE drones, they can maintain a fixed position in the stratosphere (10 to 50 km), between satellites and conventional aircrafts (Guérard, Baudin, and Hertzog 2016). HAPS can be in the form of lightweight platforms such as airplanes, airships, or balloons, and are moving rapidly toward maturity, thanks to trends in solar power, battery storage, and artificial intelligence (AI). They are designed to operate at high altitudes using solar energy but have limited payloads and cannot operate well at extreme latitudes. Some notable examples of HAPS platforms that have been in development for several years include the Airbus Zephyr platform (Robinson 2022), the BAE Phasa-35 (Thisdell 2020) and the Leonardo Skydweller (Skydweller Aero Inc 2022).

In addition to sensor improvements and lower orbits, computational techniques have emerged as a powerful tool for improving spatial resolution. Specifically, push-frame satellites, such as Planet's SkySat (Murthy et al. 2014), can observe Earth's locations multiple times, creating short videos of up to 40 frames. Subsequently, multi-image super resolution techniques can be used to increase the effective spatial resolution by a factor of 2 by merging multiple observations (Nguyen et al. 2022).

5.2. *Image accessibility and availability*

While developments of Earth observation applications have greatly benefited from open-source satellite imagery such as the Landsat and Sentinel collections, VHR imagery availability remains very restricted for the time being. Even with precise tasking, the mere definition of acquisition parameters does not ensure the retrieval of an image that is useful in terms of the presence of animals. The next advancement in this field is likely to be smart tasking, where image acquisition is predicated on the presence of specific objects within the image. Such downstream data processing services are already offered by some satellite companies[2] and can detect objects of interest such as roads and buildings, or simply alert the user about changes between two acquisition dates. These strategies could be easily extended to other objects of interest such as the presence of animals. Upstream, at the data acquisition level, AI chipsets for edge computing continue to improve (Momose, Kaneko, and Asai 2020) and may become part of the satellite payload. This strategy will both greatly reduce the bandwidth required by high temporal frequency constellations and simplify image management and tasking. Instead of providing large volumes of raw images, satellites will directly supply high-level information streams regarding events or objects of interest. Already, on-board processing with AI chips has facilitated the recognition of distinct features in an image, such as volcanic eruptions (Del Rosso et al. 2022). Intel has provided AI processing for PhiSat-1, guiding the onboard retrieval of cloud-free images and is currently being extended to flood event detection (Mateo-Garcia et al. 2021). With the advent of intelligent remote sensing (Zhang et al. 2022), we can foresee fleets of low-cost smart satellites dedicated to specific missions such as wildlife monitoring. The availability of such constellations providing open data dedicated exclusively to wildlife monitoring is critical, given the specific acquisition constraints associated to these targets (e.g. movement, low densities, unpredictable and large spatial distribution) which are not compatible with multi-application VHR missions such as WorldView, GeoEye, and QuickBird.

5.3. Survey strategy

In cases where species do not exhibit period-specific aggregation behavior, achieving a total count using VHR satellite imagery may not be feasible given the current limits of VHR satellites. Therefore, appropriate sampling methods need to be developed and should evolve simultaneously with advances in remote sensing imagery. For instance, sampling strategies might incorporate covariates (Meng et al. 2022), such as previous species distribution from ground or aerial surveys, or habitat suitability models (Singh et al. 2009) to identify locations of interest within the study area. At the moment, we assume that existing methods used in ecology may be applied or adapted in some cases. For instance, the sampling method of Jolly (1969), commonly employed in aerial survey standards (Craig 2012; Norton-Griffiths 1978), may be adapted to obtain population estimates over vast areas using satellite imagery. The sample units might be non-overlapping full images or plots selected from the latter (e.g. LaRue and Stapleton 2018; LaRue et al. 2015). Nevertheless, satellite imagery estimates should still be combined with ground efforts to ensure accurate assessment of population trends. This combination is necessary for image interpretation and because quantifying detection errors remains challenging (Ainley et al. 2015; Fretwell et al. 2012; LaRue and Stapleton 2018; LaRue et al. 2011; LaRue, Stapleton, and Anderson 2017; Pettorelli et al. 2018; Swinbourne et al. 2018; Wu et al. 2023). Furthermore, VHR satellite imagery may be used complementarily to identify and evaluate interesting or unsurveyed areas for future ground or aerial counts.

5.4. Deep learning and multimodal integration

Given the large amount of satellite data available and anticipated, there is an opportunity to build self-supervised sensor-specific models instead of simply fine-tuning pre-trained models as the availability of annotations becomes a bottleneck. One strategy is to adopt unsupervised or self-supervised techniques that allow neural networks to build better sensor-specific representations. Large datasets can be leveraged, reaching performances superior to pre-trained models (Tao et al., 2022). Generative techniques could also potentially help alleviate the lack of training samples by generating entirely new samples (Ramesh et al. 2022). Still, the same challenge remains, as most available generative models are also trained on massive proximal computer vision datasets (Koh, Fried, and Salakhutdinov 2024). In this regard, the development of specific generative models based on overhead imagery could be a promising research avenue.

Animals on satellite imagery can appear as a small group of pixels on satellite imagery. Given the results obtained by previous studies (Bowler et al. 2020; Wu et al. 2023), we argue that pixel-based object detection CNNs should provide the best detection performance for small-size (few pixels) animal detection in satellite imagery. Attractive point-based architectures developed on aerial images, and which provided good detection results for small animal detection, such as HerdNet (Delplanque et al. 2023), the seabird CNN detector of Kellenberger et al. (2021) or the sheep CNN detector of Sarwar et al. (2021), should be experimented with in the future.

The task of wildlife monitoring is inherently multimodal, with a wide range of possible data sources such as satellite, airborne, and drone imagery, as well as proximal data such as camera trap images, GNSS collars, in-situ microphones, and so on. Independently, so-called “Foundational Models,” trained on very large and diverse training sets in a self-supervised and unsupervised way, have emerged, first in natural language processing, and also in computer vision (Bommasani et al. 2022). We believe that the future of wildlife monitoring relies on such models and that future research should focus on this. Remarkably, these models are "few-shots" learners and can be readily applied to downstream tasks with very few training examples (Moor et al. 2023). Some of them are also multimodal and can handle speech, text, and computer vision, allowing the user to interact directly in text format. Large language models are providing an underlying structure to relate information from different sources and models (Shen et al. 2023). This capability is already being used in various domains, such as general medicine (Moor et al. 2023). These approaches could replicate what a photo interpreter would do when analyzing an image, taking into account a larger context of multimodal information. Pending the development of platforms that would handle multimodal data for training foundational models, large volumes of data from a wide range of sources are already available on online portals. These include for example Wildlife Insights[3] for camera trap images, Movebank[4] for wildlife GPS data and trajectories, AWIR[5] for aerial wildlife imagery, or BioAcoustica[6] for bioacoustic recordings. These data may also be cross-referenced with past satellite imagery acquisitions, providing ground truth for the development or validation of automatic methods. As a result, there is an opportunity for the emergence of specialized multimodal approaches that blend multi-sensor imagery, sound, and textual reports that can aid in the conduct of wildlife surveys.

5.5. Data and code sharing

Sharing data and code would further help the expansion and development of automated detection approaches. Moreover, building a large "wildlife satellite imagery" database similar to ImageNet or COCO is crucial and would lead to pre-trained CNN parameters, usable for various wildlife detection tasks. In this vein, Cubaynes and Fretwell (2022) have created an open-access dataset of satellite images containing annotated whales. This is bound to motivate other researchers to do the same in the near future. In recent years, multiple annotation tools have emerged, such as AIDE (Kellenberger et al. 2020) or Label-Studio (Tkachenko et al. 2020), and even a protocol to correctly annotate wildlife on satellite imagery (Cubaynes et al. 2023). Such tools should promote data sharing and collaborative work for future wildlife research. Pending an open database of wildlife satellite images or foundational wildlife models described in section 5.4, alternatives like using Web images (Chabot, Stapleton, and Francis 2022) or down-scaled aerial images should be developed (Borowicz et al. 2019).

5.6. Training and multidisciplinarity

The need for interdisciplinary integration has become obvious in the study and monitoring of biodiversity, as evidenced by the development of essential biodiversity variables (Jetz et al. 2019) and the development of global monitoring networks such as GeoBon,[7] which bring together scientists from a wide range of backgrounds. This interdisciplinary integration must continue and even be strengthened to accelerate the development of tools in this field, notably through the creation of open resources (e.g. best practices, data, code). This effort must also be reflected in the training of highly qualified personnel, through the development of more multidisciplinary programs combining geomatics, ecology, and computer science. This new generation of data scientists trained outside traditional disciplinary silos is certainly one of the most promising prospects for advancing knowledge in wildlife remote sensing.

6. Summary and conclusions

Satellite wildlife monitoring has emerged in recent years with the increasing availability of high- and very high-resolution satellite imagery. Several proofs of concepts have since demonstrated the potential of this new technology to detect large mammals or large bird colonies, mainly in open and homogeneous areas. To reduce the burden of manual interpretation, several automated image processing methods have been applied. The recent advent of deep learning opens important perspectives for increasing both the precision and the efficiency of image processing, while allowing multimodal data integration. New satellite acquisition platforms are being developed, anticipating the increasing availability of high spatial and temporal resolution. A revolution in wildlife monitoring techniques is therefore theoretically possible, but are we there yet?

The development of operational approaches that enable on-demand wildlife surveys and temporal monitoring is currently severely limited by three major bottlenecks: (1) The business model of VHR image providers is currently not adapted to wildlife studies;

(2) Current VHR satellite imagery is rarely shared, as it is limited by commercial license, even though it is essential for the development of robust machine learning approaches; (3) Training of multidisciplinary highly qualified personnel (geomatics, ecology, computer science) and interdisciplinary research is needed but still limited by traditional discipline-oriented training and communities. Once these bottlenecks are addressed, satellite wildlife remote sensing should enter a new era and will revolutionize wildlife monitoring.

Therefore, our key research priorities and recommendations are: (1) Wildlife-dedicated VHR satellite constellations should be developed and designed to offer freely available imagery at high spatial and temporal resolutions; (2) Sampling methods need to be developed and should evolve simultaneously with advances in remote sensing imagery and image processing methods; (3) Foundational DL models should be developed for processing data from various wildlife monitoring projects; (4) Initiatives to develop sharing and collaborative annotation platforms need to be further strengthened; (5) Initiatives to increase the number and quality of events, training, publications and funding programs dedicated to merge these disciplines should be encouraged.

Notes

1. https://albedo.com/
2. https://www.planet.com/products/analytics/
3. https://www.wildlifeinsights.org/
4. https://www.movebank.org/
5. https://projectportal.gri.msstate.edu/awir/
6. https://bio.acousti.ca/
7. https://geobon.org/

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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Appendix A. Overview of previous review papers' focus

Reference	Focus on animal detection/ counting/ survey	Focus on satellite imagery	Review of papers after 2018	Systematic review	All taxa	All regions
Butcher et al. (2021)			✓			✓
Clarke et al. (2021)	✓	✓	✓			✓
Corcoran et al. (2021)	✓		✓	✓	✓	✓
Delisle et al. (2023)	✓		✓	✓	✓	✓
Edney and Wood (2021)	✓		✓			✓
Goddijn-Murphy et al. (2021)	✓	✓	✓			✓
Hollings et al. (2018)	✓				✓	✓
Jiménez López and Mulero-Pázmány (2019)				✓	✓	✓
Kuenzer et al. (2014)		✓			✓	✓
Larue et al. (2017)	✓	✓			✓	✓
Linchant et al. (2015)	✓			✓	✓	✓
Nazir and Kaleem (2021)			✓		✓	✓
Pettorelli et al. (2014)		✓			✓	✓
Petrou et al. (2015)					✓	✓
Petso et al. (2021)	✓		✓		✓	✓
Sánchez-Díaz and Mata-Zayas (2019)		✓			✓	✓
Wang et al. (2019)	✓			✓	✓	✓
Weinstein and Prugh (2018)	✓			✓	✓	✓

Appendix B. List of papers selected for the systematic review

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