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REVIEW

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A computer vision for animal ecology

Ben G. Weinstein

Department of Fisheries and Wildlife, Marine Mammal Institute, Oregon State University, Newport, OR, USA

Correspondence
Ben G. Weinstein
Email: weinsteb@oregonstate.edu

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Abstract

1. A central goal of animal ecology is to observe species in the natural world. The cost and challenge of data collection often limit the breadth and scope of ecological study. Ecologists often use image capture to bolster data collection in time and space. However, the ability to process these images remains a bottleneck.
2. Computer vision can greatly increase the efficiency, repeatability and accuracy of image review. Computer vision uses image features, such as colour, shape and texture to infer image content.
3. I provide a brief primer on ecological computer vision to outline its goals, tools and applications to animal ecology.
4. I reviewed 187 existing applications of computer vision and divided articles into ecological description, counting and identity tasks.
5. I discuss recommendations for enhancing the collaboration between ecologists and computer scientists and highlight areas for future growth of automated image analysis.

KEYWORDS

automation, camera traps, ecological monitoring, images, unmanned aerial vehicles

1 | INTRODUCTION

Observing biodiversity can be expensive, logistically difficult and time-consuming. Many animals are rare, secretive and inhabit remote areas. Animal presence and behaviour may vary over broad spatial and temporal scales, and depend on important but infrequently observed events, such as breeding, predation or mortality. Direct observation of these events can be disruptive to wildlife, and potentially dangerous to observers. To reduce cost, labour and logistics of observation, ecologists are increasingly turning to greater automation to locate, count and identify organisms in natural environments (Pimm et al., 2015). While image capture has greatly increased sampling, our ability to analyse images remains a bottleneck in turning these data into information on animal presence, abundance and behaviour. Computer vision can increase the breadth, duration and repeatability of image-based ecological studies through automated image analysis (Dell et al., 2014; Kühl & Burghardt, 2013; Pennekamp & Schtickzelle, 2013). Computer vision is a form of image-based computer science that uses pixel values to infer image content (LeCun, Bengio, & Hinton, 2015). The atomic unit of data in computer vision is an image pixel that represents colour in the visible spectrum. Pixels are arranged into groups such that pixel proximity, orientation and similarity create a group identity. Pixel values, and the resulting group identity, may change among images to create a sequence of objects. By creating rules for the pixel characteristics, relationships and changes through time, computer vision algorithms can replace laborious hand-review of ecological images.

The growth in ecological image data is fuelled by its economy, efficiency and scalability (Bowley, Andes, Ellis-Felege, & Desell, 2017; Dell et al., 2014). Massive repositories of image data are available for ecological analysis, uploaded from field-based cameras (Giraldo-Zuluaga, Gomez, Salazar, & Diaz-Pulido, 2017; Swanson et al., 2015; Zhang, He, Cao, & Cao, 2016) or captured by citizen scientists (Desell et al., 2013; Joly et al., 2014). For example, research grade datasets

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from iNaturalist (675,000 images of 5,000 species, Van Horn et al., 2017) and Zooniverse (1.2 million images of 40 species; Swanson et al., 2015), highlight the growth in high-quality images captured by researchers and the public. However, image data collection has greatly outpaced image analysis tools. While a human may be better at finding animals in time-lapse video (Weinstein, 2015), or have a greater knowledge of bird identification (Berg et al., 2014), when confronted with 100,000 images, it is difficult to find the time, organization and concentration to validate each image manually. My aim is to describe the ongoing work in utilizing computer vision for animal ecology, provide a brief description of the concepts that unite computer vision algorithms, and describe areas for collaboration and growth with the computer vision community.

2 | APPLICATIONS OF COMPUTER VISION TO ANIMAL ECOLOGY

Ecological computer vision has grown out of multiple disciplines, with contributions from computer science (Branson, Van Horn, Belongie, & Perona, 2014), astronomy (Arzoumanian, Holmberg, & Norman, 2005) and remote sensing (LaRue, Stapleton, & Anderson, 2016). This article covers applications of computer vision to find, count and study animals in natural landscapes using images collected in the human visual spectrum. Applications from specimen morphometrics, microscopy (Pennekamp & Schtickzelle, 2013) and animal tracking in laboratory settings are reviewed elsewhere (Dell et al., 2014; Robie, Seagraves, Egnor, & Branson, 2017). To find articles, I used Web of Science to search for “Computer Vision AND (Ecology OR Animals),” yielding 284 articles. I then performed three additional searches for articles using image analysis tools, but lacking the computer vision label: “Automated species measurement AND images” (*n* = 103), “Automated species detection AND images” (*n* = 126) and “Automated species identification AND images” (*n* = 196). Finally, I reviewed the first 200 results from Google Scholar for “Computer Vision AND ecology” published since 2000. For all searches, articles were included based on the following criteria.

1. The article described a peer-reviewed application of computer vision. Articles introducing hardware for image capture, or reviewing existing applications, were excluded.
2. The article was aimed at answering an ecological question, broadly defined as the identity, demography and behaviour of animals in natural environments using images collected in human visual spectrum.
3. The application used an automated or semi-automated image analysis algorithm. Articles using manual review of images were excluded.

This search and filtering criteria resulted in 187 articles, with consistent growth in computer vision applications over time (Figure 1). These articles used a variety of open source tools to aid image analysis (Table 1). I organized articles around three common tasks for ecological computer vision: description, counting and identification (Figure 2). From the perspective of image-based computer vision, description is the quantification of the coloration, patterning and relative size of animals and their immediate surrounding environment. Counting is the detection and enumeration of animals within an image. Identity is the classification of an individual or species based on its appearance. For each of these tasks, my goal is to help ecologists grasp the current possibility for image automation by introducing basic terminology, applications and highlighting a case study.

3 | DESCRIPTION

Ecologist often seek to understand animal appearance and their relationship to the surrounding environment using digital observations. The secretive nature of many animals makes direct description disruptive and potentially dangerous to both the organism and researcher. Computer vision algorithms have greatly increased the ability to non-invasively measure organisms through image analysis (*n* = 56). To ascertain the size, position and spectral characteristics of ecological objects in images, computer vision tools use image features (see Box 1) to find important pixels within and among images. Image features are often areas of high turnover in pixel values, caused by edges of objects of interest. For example, to correctly outline a flying bird, algorithms might look for the areas where the wings intersect with the sky (Atanbori, Duan, Murray, Appiah, & Dickinson, 2016). Image features have been primarily used to study the evolutionary ecology of animal coloration (Stoddard, Kilner, & Town, 2014), shape (Lavy et al., 2015) and patterning (Levy, Lerner, & Shashar, 2014). Compared to human review, computer vision provides a more consistent way to score animal appearance across images by using non-RBG colour spaces, such as HSV or YChCr, which are less sensitive to changes in illumination and other image artefacts (Kühl & Burghardt, 2013; Troscianko, Skelhorn, & Stevens, 2017). By comparing image features, computer vision can be used to study animal camouflage (Tankus & Yeshurun, 2009) and biomimicry (Yang, Wang, Liang, & Møller, 2016). For example, Stoddard et al. (2016) developed edge detection algorithms to evaluate the relative camouflage of nesting shorebird species as compared to their nesting substrate (Figure 3b).

Image features can also be used to measure size in both specimens and free-living animals (Olsen & Westneat, 2015). Based on multiple images from pairs of cameras, computer vision tools have been used to describe animal size and shape, such as in whales (Howland, Macfarlane, & Tyack, 2012), and coral (Jones, Cantin, Berkelmans, Sinclair, & Negri, 2008; Naumann, Niggl, Laforsch, Glaser, & Wild, 2009). The next frontier for image-based ecological description is in 3D reconstruction of morphology and movement (Haggag, Abobakr, Hossny, & Nahavandi, 2016; Lavy et al., 2015). Three-dimensional imaging has recently been used to track animal behaviour within large indoor enclosures (e.g. Barnard et al., 2016), and applying these tools to animals in natural landscapes is an developing area of research (Robie et al., 2017).

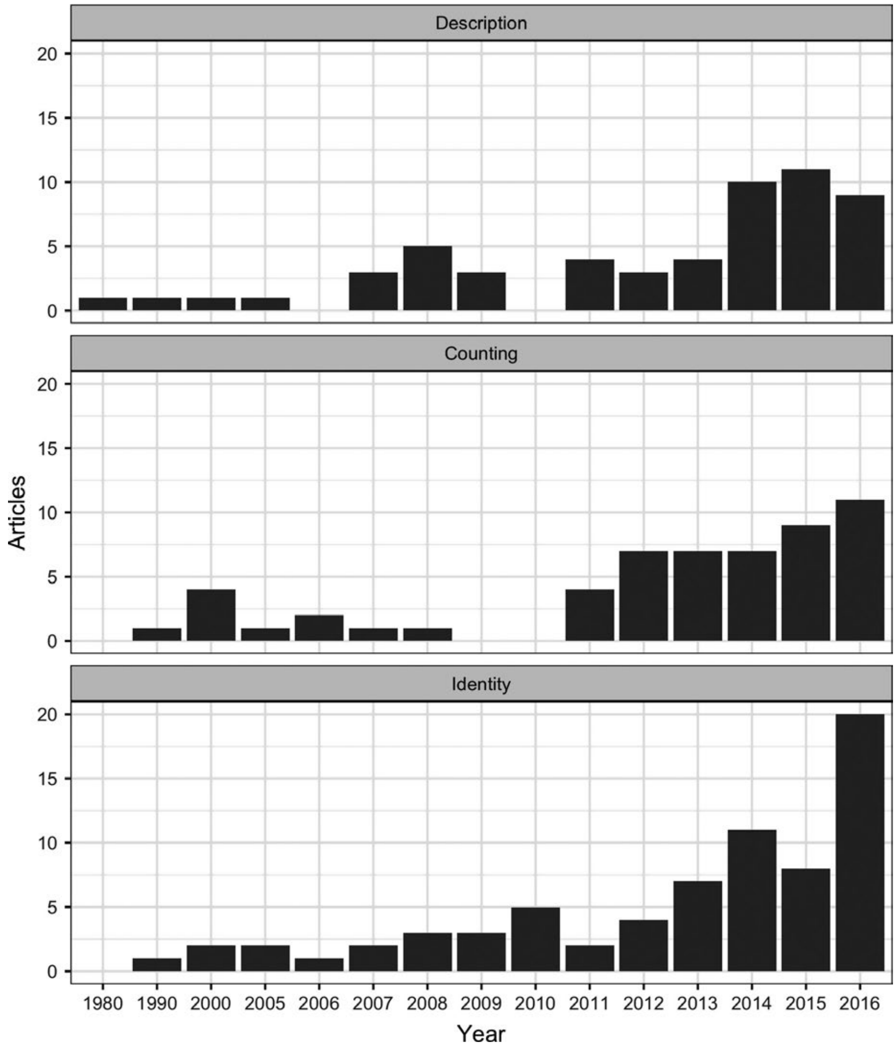

FIGURE 1 The growth in computer vision applications over time (n = 187). From the perspective of image-based computer vision, description is the quantification of image features to describe coloration, patterning and relative size of animals and their surrounding habitat. Counting is the detection and enumeration of animals within an image. Identity is the classification of an individual or species based on its appearance

TABLE 1 Commonly used tools for computer vision application to ecology

Name	Reference	Task	Comments
OpenCV	Bradski (2000)	Description, Counting, Identity	Source library for computer vision algorithms in python/java/C++
ImageJ	Abràmoff et al. (2004)	Description, Counting	Segmentation and thresholding
BISQUE	Kvilekval et al. (2009)	Description, Counting	Also serves as a hosting platform for image analysis tools
Agisoft Photoscan	–	Description	Commercial software for 3D model reconstruction from images
StereoMorph	Olsen and Westneat (2015)	Description	R package for 3d reconstruction and image calibration
NaturePatternMatch	Stoddard et al. (2014)	Description	Comparing features among ecological images
MotionMeerkat	Weinstein (2015)	Counting	Background subtraction for animal detection in videos and images.
Google Cloud API	–	Identity	Classification of image content using Cloud Vision API, deep learning source library using TensorFlow
Merlin	Van Horn et al. (2015)	Identity	Bird identification app for iPhone and Android
Wildbook	Crall et al. (2013)	Identity	Individual identification and data management tools

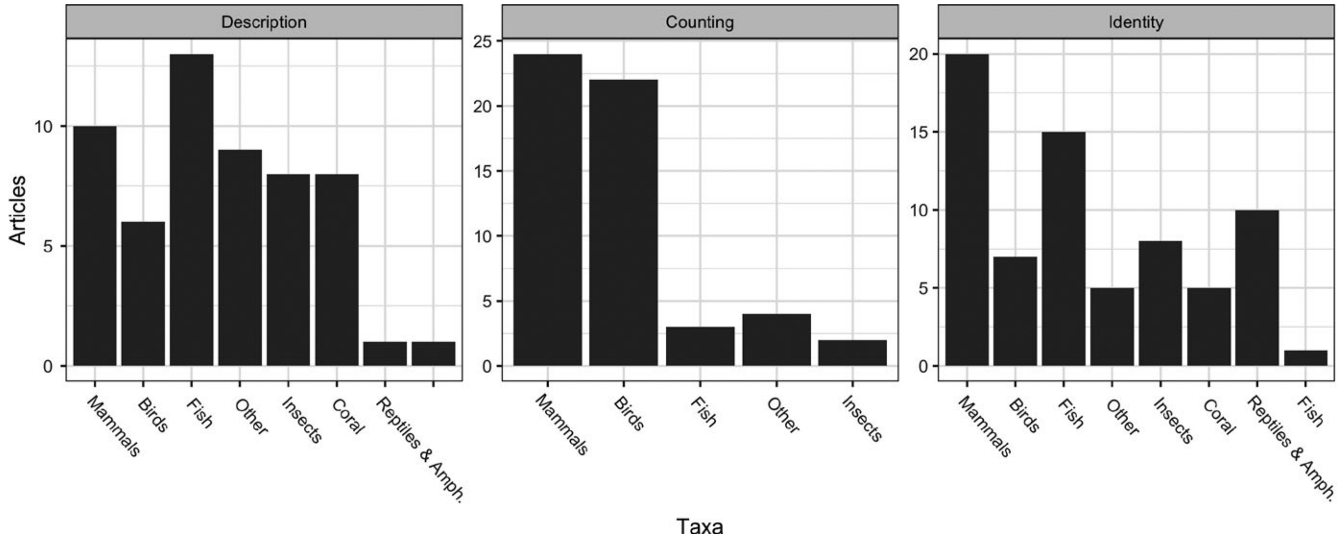

FIGURE 2 The number of ecological computer vision articles (n = 187) for each focal taxa and computer vision task. From the perspective of image-based computer vision, description is the quantification of image features to describe coloration, patterning and relative size of animals and their surrounding habitat. Counting is the detection and enumeration of animals within an image. Identity is the classification of an individual or species based on its appearance

Box 1 Glossary of key computer vision terms for ecological image analysis

Description

Features: Pixel properties based on the colour, texture, or relationship to surrounding pixels.

Colour space: Numeric system used to describe the spectral information contained in pixel values.

Edges: Image locations with abrupt changes in pixel values, also known as 'corners'. Often used to find corresponding points between images.

Structure-from-motion: Approach for reconstructing the 3D structure of a stationary object based on stitching together images taken from multiple angles.

Optical flow: The identification of analogous pixels among images, used to track object or camera movement.

Counting

Segmentation: The process of partitioning images into labelled regions.

Contours: Curved lines which encompass connected pixels with similar colour, intensity or texture.

Blobs: Groups of connected pixels with a fixed identity or label.

Image morphology: Image processing tools for manipulating pixels based on the values of the surrounding pixels. For example, 'opening' reduces noise in the foreground by removing weakly connected pixels.

Background subtraction: The removal of irrelevant content estimated from multiple frames of video. Subtracting the static portions of the frame from the current image yields the estimated foreground objects.

Identity

Labelled training data: Images with known objects of interests that can be used to train machine learning classifiers.

Unsupervised classification: Multidimensional clustering algorithms to divide pixels into an a priori number of groups based on image features.

Neural-network or 'deep learning': A hierarchical machine learning classifier that uses training data to categorize image content without a priori specification of image features.

3.1 | Case study: High-resolution mapping of penguin colonies using structure-through-motion

To map habitat suitability, ecologists often use remotely sensed environmental variables as a proxy for the environmental conditions encountered by animals. While traditional remote sensing captures coarse changes in habitat quality, animals experience the environment at fine-scales, in three dimensions, and from a landscape perspective. McDowall and Lynch (2017) generated ultra-fine scale (<1 cm) maps of penguin colonies by stitching together thousands of overlapping images using a technique called structure-from-motion. The resulting three-dimensional surface allowed fine-scale mapping of Gentoo penguin (*Pygoscelis papua*)

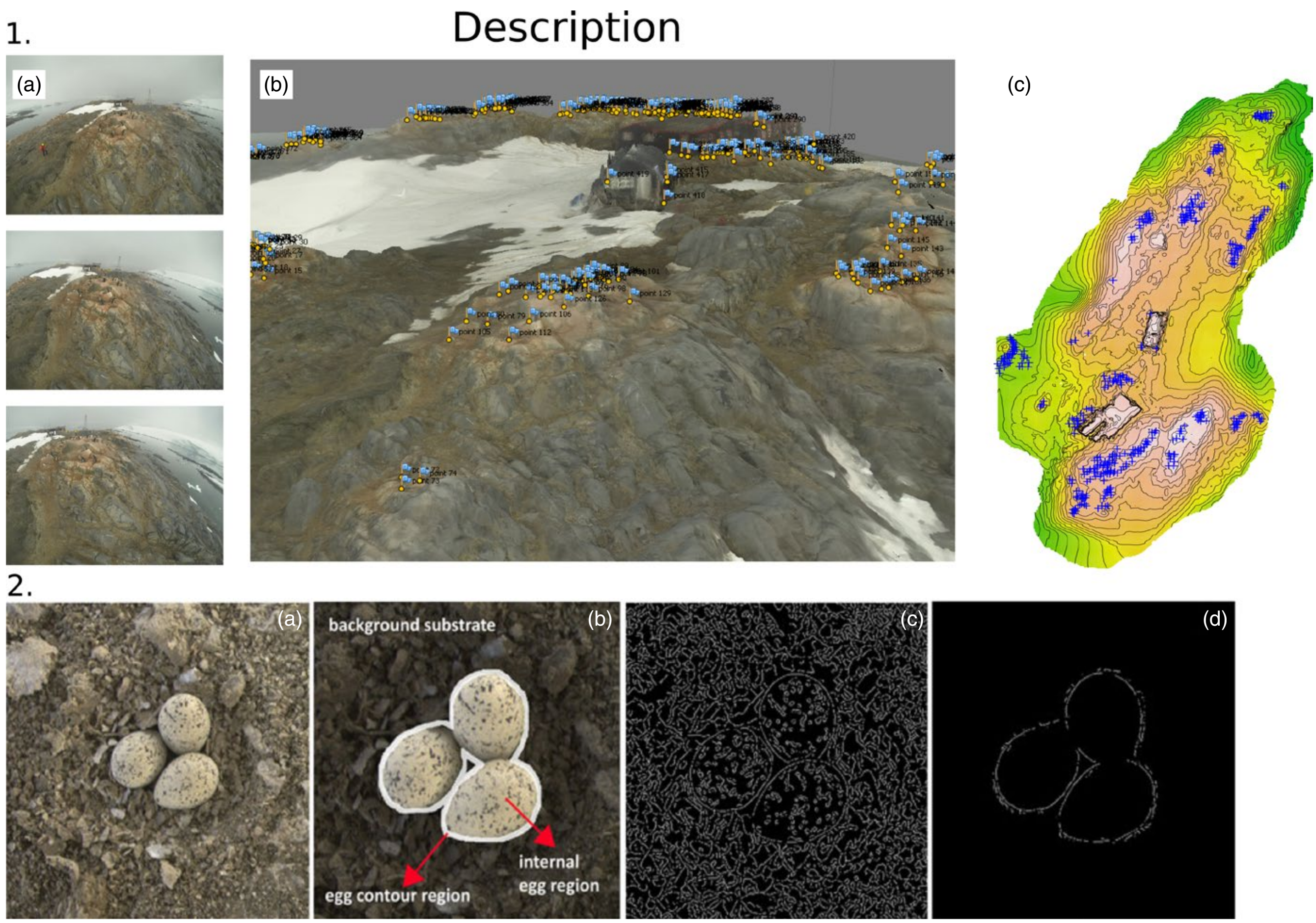

FIGURE 3 Applications of computer vision to describing ecological objects. (1) From McDowall and Lynch (2017), a three-dimensional map of the Port Lockroy penguin colony was created by overlaying hundreds of individual photographs (1a) to describe the location of Gentoo penguin (*Pygoscelis papua*) nests (1b). Flags denote occupied penguin nests identified in the images. The surface was turned into digital elevation map (1c) to measure the relative positive and habitat choice by individual penguins for nest site selection. (2) From Stoddard et al. (2016), snowy plover (*Charadrius nivosus*) nest clutch (2a) segmented into egg and background regions (2b), edge detection was used to quantify edges (2c), in order to calculate the degree of egg camouflage compared to the background substrate (2d). See Acknowledgements for credits and permissions [Colour figure can be viewed at wileyonlinelibrary.com]

nests and captured variation in slope and aspect that may have been missed by coarser satellite-based remote sensing (Figure 3a).

4 | COUNTING

While remotely placed cameras provide a low-cost alternative to human observers, the amount of data generated by field studies can be overwhelming. The potentially high cost of image review and storage means that finding the animals of interest within large batches of images can improve the speed and efficiency of biodiversity monitoring. Even motion triggered camera traps suffer from many false-positive images due to wind and moving vegetation. In computer vision, finding novel objects within series of images can be achieved using background subtraction, which distinguishes sedentary objects, such as trees and clouds, from moving objects, such as animals, within videos or groups of images (Price Tack et al., 2016; Ren, Han, & He, 2013; Weinstein, 2015) (Figure 4a). A background model is created by computing an expected image based on the previous pixel values (Stauffer & Grimson, 1999). The foreground model describes the non-background pixels as a function of the difference between the previous background model and the current frame (Figure 4a; Christiansen, Nielsen, Steen, Jørgensen, & Karstoft, 2016; Sobral & Vacavant, 2014). The background model changes over time based on new pixel values, thereby reducing false positives from shifts in illumination and external movement, such as wind, waves or camera shake. Once images have been divided into foreground and background pixels (known as segmentation), objects are partitioned into discrete groups, with connected sets of pixels corresponding to individual organisms.

I found 55 articles that used a form of background subtraction to detect and count animals, primarily for mammals (n = 24) and birds (n = 22). These studies report high accuracy in removing empty frames, but there were persistent challenges in reducing false positives from strong wind and other extraneous movement in heterogeneous environments (Price Tack et al. 2016). Tailoring detection algorithms to individual taxa can greatly improve accuracy, for example, Zeppelzauer (2013) reported

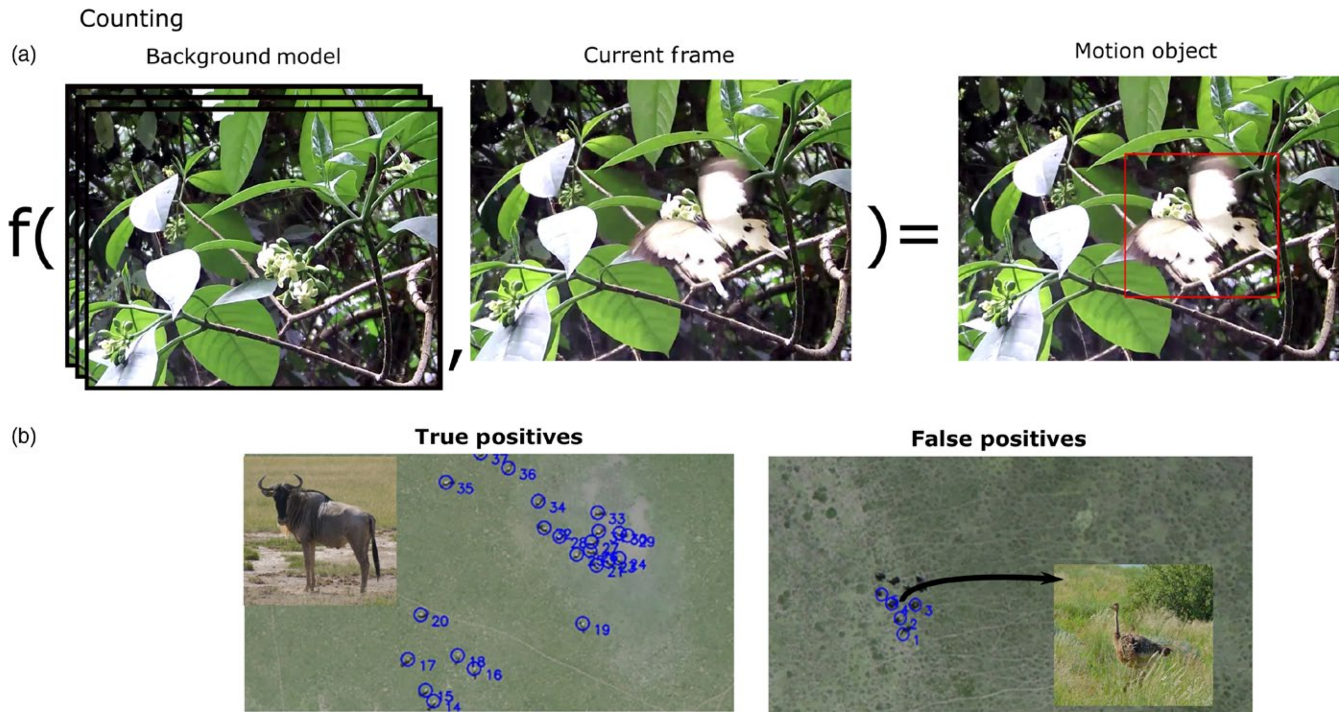

FIGURE 4 Applications of computer vision to detecting and counting ecological objects. (a) Background subtraction of video frames yields the desired motion object (Weinstein, 2015) based on changes in past pixel values. (b) Counting wildebeest from imagery captured by unmanned aerial vehicle in Tanzania (Torney et al., 2016). The left panel are correct identifications of wildebeest, the right panel are false positives caused by a flock of juvenile ostrich. See Acknowledgements for credits and permission [Colour figure can be viewed at wileyonlinelibrary.com]

>95% accuracy in detecting African elephants (*Loxodonta cyclotis*) by building a colour model from training data. State-of-the-art approaches (Ren et al., 2013; Zhang et al., 2016) can both identify images of interest, as well as define where within an image an animal occurs. This is a crucial first step in cropping photos to analyse species identity (see below).

New computer vision tools have opened new avenues for image data collection. Automated count data have been taken from time-lapse video (Steen & Ski, 2014), camera traps (Matuska, Hudec, Kamencay, Benco, & Zachariasova, 2014), uploaded by citizen scientists (Kosmala et al., 2016) and captured from airborne sensors (van Andel et al., 2015). In particular, automated detection algorithms are increasingly used to find large animals within remotely sensed imagery captured by high-resolution commercial satellites (Barber-Meyer, Kooyman, & Ponganis, 2007) and unmanned aerial vehicles (Hodgson, Kelly, & Peel, 2013; Liu, Chen, & Wen, 2015; van Andel et al., 2015). Commercial satellite imagery offers wide spatial coverage at sub-metre resolution, but is limited by atmospheric conditions, temporal coverage and high cost. To find animals within this imagery, studies have used pixel-based analysis (Fretwell, Staniland, & Forcada, 2014), image differencing (LaRue et al., 2015) and supervised classification using machine learning (Yang et al., 2014). Several applications focus on aggregations of individuals in colonial breeding sites due to their large spatial size and distinct visual signature on the surrounding environment (Barber-Meyer et al., 2007; Lynch, White, Black, & Naveen, 2012). While results from Southern right whales (*Eubalaena australis*) (Fretwell et al., 2014), polar bears (*Ursus maritimus*) (LaRue et al., 2015), and savanna ungulates (Yang et al., 2014) highlight the promise of this technology, considerable automation is needed to reduce the laborious hand validation of images at scale (LaRue et al., 2016).

In comparison to satellite-based imagery, unmanned aerial vehicles have the advantages of greater temporal flexibility and low cost (Seymour, Dale, Hammill, Halpin, & Johnston, 2017). The trade-off is the decreased spatial extent limited by flight time and legal restrictions (Crutsinger, Short, & Sollenberger, 2016). UAVs have been successfully used to count waterbird populations, due to the birds' open habitat and colonial breeding strategy (Descamps, Béchet, Descombes, Arnaud, & Zerubia, 2011; Groom, Krag Petersen, Anderson, & Fox, 2011). Chabot and Francis (2016) reported that automated counts of waterbirds were within 3%–5% of human counts across 16 applications. Recent improvements of UAV-based counting include utilizing hyperspectral data (Beijboom et al., 2016; Witharana & Lynch, 2016), pixel-shape modelling (Liu et al., 2015) and combining background subtraction with machine learning (Torney et al., 2016) (Figure 4b). Recent efforts to count animals use deep learning neural networks are promising, but require tens of thousands of training images gathered by human annotation (Bowley et al., 2017).

4.1 | Case study: Counting hummingbird–plant interactions using background subtraction

To predict the rules that determine the interactions among species, ecologists often use the frequency of interactions as a proxy for fitness effects (Bartomeus et al., 2016). To determine the number of visits between birds and flowers, Weinstein and Graham (2017) used time-lapse cameras to film multiple days of flower visitation. Using

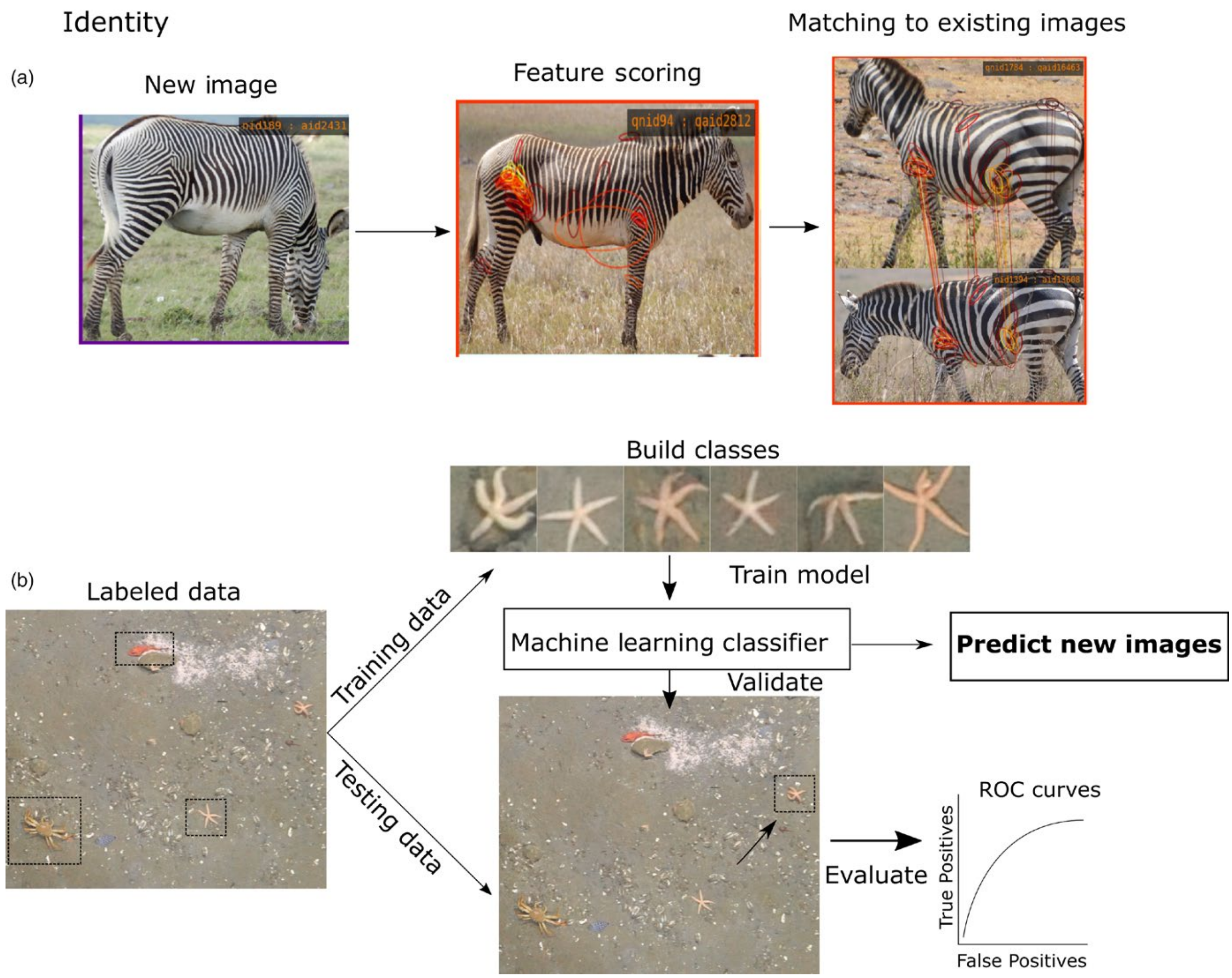

FIGURE 5 Application of computer vision to predicting individual and species identity: (a) Matching algorithms score the similarity of photographed zebras to a library of known images to track individuals over time (Crall et al. 2013). (b) From Marburg and Bigham (2016), a deep learning classifier is trained on a starfish species class based on training data of labelled images. The classifier is then used to predict testing data to evaluate the accuracy of the approach. In this example, the training and testing data are separate objects within the same image frame based on bounding boxes that distinguish animals from the image background. See Acknowledgements for image credits and permissions [Colour figure can be viewed at wileyonlinelibrary.com]

background subtraction algorithms, they were able to process over 8,000 hr of hummingbird visitation videos (Weinstein, 2015). This video-based strategy allowed sampling at much greater temporal extents, and therefore minimized the potential for overlooking rare interactions. From these data, the authors modelled species interactions based on morphological similarity and flower abundance to test predictions of optimal foraging theory (Weinstein & Graham, 2017).

5 | IDENTITY

Ecologists often need to inventory the diversity of taxa or the number of individuals of a given species in a geographic area. The strong relationship between sampling duration and observed species richness means that data collection can often be expensive and logistically challenging. Image-based animal classification has the potential to reduce costs, allow greater geographic coverage and cause less disturbance to potentially sensitive ecosystems.

For individual-level identification, computer vision algorithms use images of known individuals to match new images based on the similarity of phenotypic patterns (Figure 5a). By matching the image features among images, matching algorithms score the likelihood that two images are of the same individual. For animals with unique markings, this can be a low-cost alternative to expensive trapping and tagging programs. This approach was pioneered for fluke identification in marine mammals (Adams, Speakman, Zolman, & Schwacke, 2006; Beekmans, Whitehead, Huele, Steiner, & Steenbeek, 2005; Gilman, Hupman, Stockin, & Pawley, 2016) and has since been applied on a wide range of taxa, from zebras (*Equus grevyi*) (Crall, Stewart, Berger-Wolf, Rubenstein, & Sundaresan, 2013), to elephants (*L. cyclotis*) (Ardovini, Cinque, &

TABLE 2 Evaluation statistics for recent computer vision applications to predicting species-level identity. Articles shown only include applications to more than five species and quantified the classification accuracy using a testing dataset. Accuracy is only reported for the best performing model in each paper. Articles are ordered by publication date

Reference	Training images	Taxa	Species or classes	Average accuracy (%)
Wilber et al. (2013)	5,362	Mammals, Reptiles	7	76.4
Yu et al. (2013)	22,533	Mammals	18	83.8
Chen, Han, He, Kays, & Forrester (2014)	9,530	Rainforest Mammals	19	38.3
Hernández-Serna et al. (2014)	1,800	Fish, Butterflies	32	92.87
	92		11	93.25
Atanbori et al. (2016)	–	Birds	7	89.0
Berg et al. (2014)	Avg. of 200 per species	Birds	500	66.6
Beijboom et al. (2016)	28,400	Coral	10	88.9
Marburg & Bigham (2016)	8,586	Benthic invertebrates and fish	10	89.0
Gomez et al. (2016)	14,346	Savanna animals	26	88.9
Qin, Li, Liang, Peng, & Zhang (2016)	22,370	Fish	23	98.6
Villon et al. (2016)	1,400	Fish	8	65.8
Sun et al. (2017)	9,160	Fish	15	77.27
Feng et al. (2016)	4,530	Moths	50	53.12

Sangineto, 2008), and box turtles (*Terrapene carolina*) (Cross, Lipps, Sapak, Tobin, & Root, 2014). These methods are effective in identifying animals with complex markings, such as giraffes (*Giraffa camelopardalis*) (Bolger, Morrison, Vance, Lee, & Farid, 2012), whale sharks (*Rhincodon typus*) (Arzoumanian et al., 2005) and catfish (*Rineloricaria aequalicuspis*) (Dala-Corte, Moschetta, & Becker, 2016), and range from completely automated (Town, Marshall, & Sethasathien, 2013), to involving human feedback during matching (Duyck et al., 2015). Crall et al. (2013) reported accuracy rates ranging from 95% for Grey's zebras (*E. grevyi*) to 100% for jaguars (*Panthera onca*) using the HotSpotter algorithm, which can be accessed through the Wildbook web platform.

Automated species identification is rapidly developing field with an explosion of new approaches and promising results (Figure 5b). While initial attempts focused on traditional machine learning with an a priori division of image features (e.g. Blanc, Lingrand, & Precioso, 2014; Lytle et al., 2010), the accuracy of these approaches was generally low (>70%). However, recent advances using new deep learning models have greatly improved model performance across a wide variety of animal taxa, from coral (Beijboom et al., 2016) to large mammals (Gomez, Diez, Salazar, & Diaz, 2016) (Table 2). The majority of applications I reviewed had a particular geographic focus, for example the rodent community of the Mojave desert (Wilber et al., 2013). The next stage is a general test of machine learning models across systems to find the optimal number of training images, model parameters and the required spectral diversity of potential classes that leads to increased predictive performance (Van Horn et al., 2015).

5.1 | Case study: Merlin, a bird identification app powered by deep learning neural networks

The Merlin project demonstrates the potential for revolutionary change in ecological identification (Farnsworth et al., 2013). Merlin is the joint project from Visipedia and the Cornell Laboratory of Ornithology to identify 600 common North American bird species (Van Horn et al., 2015). The identification algorithm uses Google's TensorFlow deep learning platform, as well as citizen science data from eBird to generate potential species lists given a user's location (Branson et al., 2010). While Merlin is primarily geared towards citizen scientists, pairing this technology with the growing number of publically accessible photos (e.g. iNaturalist.org) promises to bolster observations of rare and cryptic species for biodiversity monitoring.

6 | COLLABORATION WITH COMPUTER VISION RESEARCHERS

The combination of high-quality data, applied use cases and interesting problems will lead to productive collaborations among ecologists and computer vision researchers. While computer vision tools are becoming more accessible to ecologists, state-of-the-art solutions will benefit from collaboration with the computer vision community. Finding and maintaining these collaborations can be difficult given the difference in terminology and aims of ecologists vs. computer science researchers. I suggest highlighting three areas of potential mutual interest:

1. Ecology has intriguing and challenging technical problems. The natural world is complex and heterogeneous. Changes in illumination and backgrounds make animal detection difficult. Changes in organism appearance and shape are challenging for classification algorithms. Ecologists should emphasize the generality of their proposed problem, and frame collaborations as a potential area for development of new algorithms, rather than as an applied example.

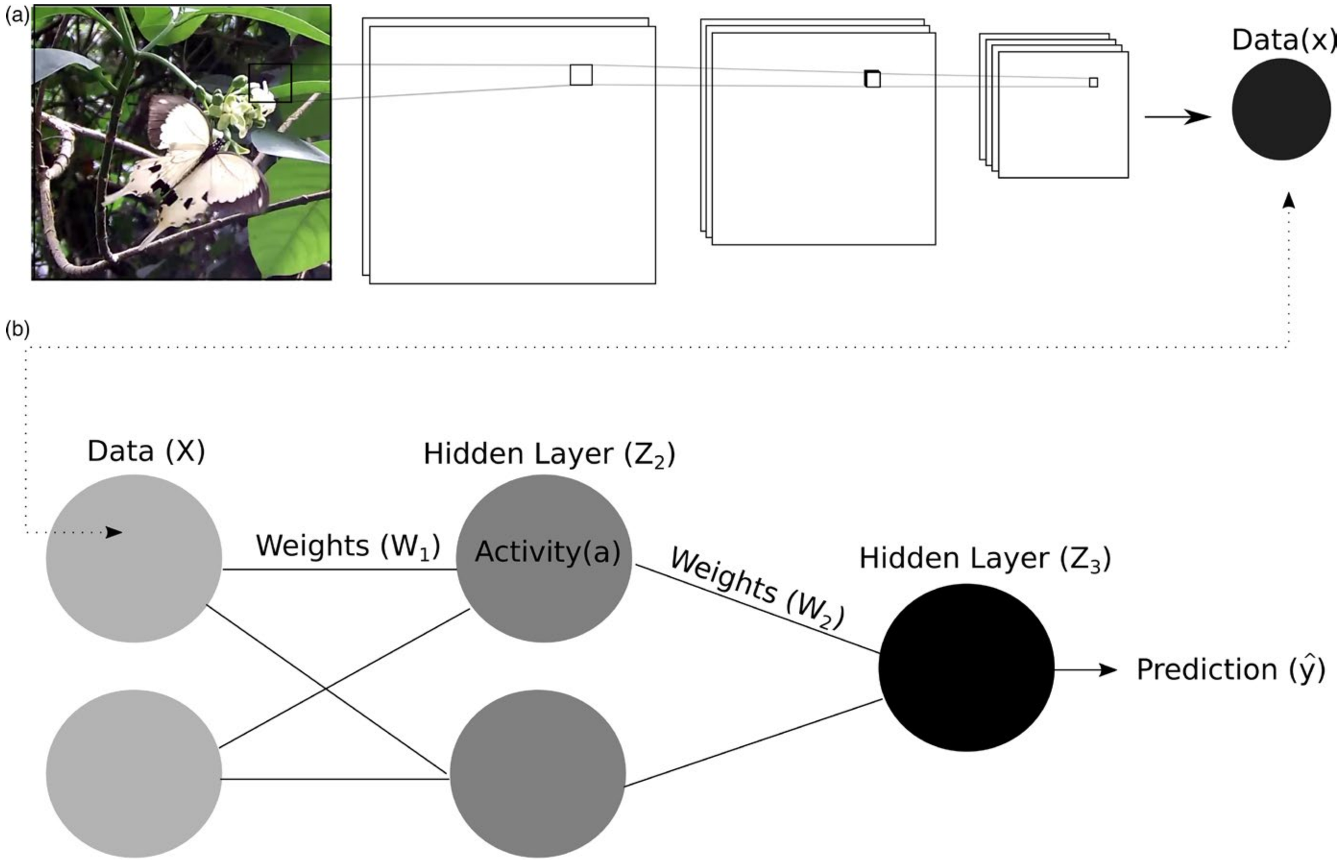

FIGURE 6 Overview of a neural network for machine learning prediction: (a) Pixel convolutions create combinations of input predictors by down sampling and pooling image features, (b) a generic deep learning structure, input data passes through hidden layers, called nodes, to create pathways from predictors to prediction. The activation score at each of these nodes is used to estimate model weights. In current deep learning applications, there will be many hidden layers of nodes to create combinations of input predictors [Colour figure can be viewed at wileyonlinelibrary.com]

2. Ecologists can improve computer vision algorithms by providing biological context (Berg et al., 2014). Ecological rules that may seem to be common sense, such as "there should not be fish on land," require neural networks to identify both objects in an image ("fish"), scene context ("land") and the relationship between image features. One way to overcome this would be to cumbersomely train an algorithm with thousands of images of land without fish. Ecology provides a more straightforward and effective method by using image metadata, such as time or location, to assist in image classification. For example, combining image location with expert vetted species regional checklists might show that only a few species with a given coloration occur in given location. Similarly, image context can assist future predictions. For example, if an algorithm identifies a wildebeest in an aerial image, it may be more likely to also find zebras (Swanson et al., 2015). Finally, ecological context can reduce the burden of gathering training data by exploiting the inherent conservation of body plans among animals to create hierarchical labels. Rather than thinking of all potential individual categories (e.g. black bear, grizzly bear, polar bear, etc.), hierarchical labelling exploits the connections among animals to create nested categories (e.g. *Ursus*). Tree-based classification approaches have been effective in other areas of computer vision, and fits naturally with the study of evolutionary taxonomy (Favret & Sieracki, 2016).
3. Ecologists are collecting vast amounts of labelled data. Computer vision applications, and especially deep learning approaches, require significant training and testing data. High-quality datasets are difficult to find, and a lack of labelled data is a major obstacle in computer vision research (Belongie & Perona, 2016; Berg et al., 2010; Gomez et al., 2016). Packaging image datasets and making them publicly available will raise awareness of the opportunities for ecological collaboration.

7 | FUTURE GROWTH

The future of ecological computer vision will combine new algorithms, data and collaborations to study animals in natural environments. The rise of neural networks as the central tool in image classification (Gomez et al., 2016; LeCun et al., 2015), background subtraction (Christiansen et al., 2016) and image description (Mohanty, Hughes, & Salathé, 2016) is a key development that with bring new opportunities for ecological computer vision (Figure 6). Until recently, the growth of these tools has been slowed by a lack of access to cutting edge algorithms. The recent unveiling of the Google Cloud Machine Learning platform could be a quantum leap in access for ecologists. Released in 2016, Google gives users access to a web service to retrain models using Google's popular TensorFlow software. TensorFlow is a computational graph algorithm that represents mathematical operations as nodes and stores data in multidimensional arrays. Rather than building a model from scratch for each application, users can retrain pre-built models to add new image classes. Known as transfer learning, this approach uses the strengths of the underlying architecture, but adds flexibility for specialized problems. This greatly reduces the time and expertise needed to implement image analysis solutions.

A persistent challenge in computer vision applications is collecting sufficient labelled data (Berg et al., 2010). New data collection opportunities through data mining (Zhang, Korayem, Crandall, & Lebuhn, 2012) and citizen scientists will broaden the potential sources of labelled ecological data (Swanson, Kosmala, Lintott, & Packer, 2016). The natural excitement for plants and animals means that gathering further labelled data is possible through online citizen scientist efforts (Van Horn et al., 2015). In particular, projects on the Zooniverse, iNaturalist and Wildlife @home web platforms provide a way of engaging important user communities (Desell et al., 2013; Kosmala et al., 2016). The next step is integrating citizen scientists as a part of greater automation, rather as an alternative to automation. Known as "human in loop" approaches, this strategy can learn directly from human annotations to provide feedback and recommendation for future data labelling (Branson et al., 2010; Reda, Mateevitsi, & Offord, 2013). This will combine the expertise and excitement from citizen scientists, with the greater standardization of automation.

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DATA ACCESSIBILITY

Data available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.b700h (Weinstein, 2017).

ORCID

Ben G. Weinstein http://orcid.org/0000-0002-2176-7935

REFERENCES

Abràmoff, M. D., Magalhães, P. J., & Ram, S. J. (2004). Image processing with imageJ. *Biophotonics International*, *11*, 36–41. https://doi.org/10.1117/1.3589100

Adams, J. D., Speakman, T., Zolman, E., & Schwacke, L. H. (2006). Automating image matching, cataloging, and analysis for photo-identification research. *Aquatic Mammals*, *32*, 374–384. https://doi.org/10.1578/AM.32.3.2006.374

Ardovini, A., Cinque, L., & Sangineto, E. (2008). Identifying elephant photos by multi-curve matching. *Pattern Recognition*, *41*, 1867–1877. https://doi.org/10.1016/j.patcog.2007.11.010

Arzoumanian, Z., Holmberg, J., & Norman, B. (2005). An astronomical pattern-matching algorithm for computer-aided identification of whale sharks *Rhincodon typus*. *Journal of Applied Ecology*, *42*, 999–1011. https://doi.org/10.1111/j.1365-2664.2005.01117.x

Atanbori, J., Duan, W., Murray, J., Appiah, K., & Dickinson, P. (2016). Automatic classification of flying bird species using computer vision techniques. *Pattern Recognition Letters*, *81*, 53–62. https://doi.org/10.1016/j.patrec.2015.08.015

Barber-Meyer, S. M., Kooyman, G. L., & Ponganis, P. J. (2007). Estimating the relative abundance of emperor penguins at inaccessible colonies using satellite imagery. *Polar Biology*, *30*, 1565–1570. https://doi.org/10.1007/s00300-007-0317-8

Barnard, S., Calderara, S., Pistocchi, S., Cucchiara, R., Podaliri-Vulpiani, M., Messori, S., & Ferri, N. (2016). Quick, accurate, smart: 3D computer vision technology helps assessing confined animals' behaviour. *PLoS ONE*, *11*, 1–20. https://doi.org/10.1371/journal.pone.0158748

Bartomeus, I., Gravel, D., Tylianakis, J. M., Aizen, M., Dickie, I., & Bernard-Verdier, M. (2016). A common framework for identifying rules across different types of interactions. *Functional Ecology*, *10*, 1–40. https://doi.org/10.1111/1365-2435.12666

Beekmans, B. W. P. M., Whitehead, H., Huele, R., Steiner, L., & Steenbeek, A. G. (2005). Comparison of two computer-assisted photo-identification methods applied to sperm whales (*Physeter macrocephalus*). *Aquatic Mammals*, *31*, 243–247. https://doi.org/10.1578/AM.31.2.2005.243

Beijboom, O., Treibitz, T., Kline, D. I., Eyal, G., Khen, A., Neal, B., … Kriegman, D. (2016). Improving automated annotation of benthic survey images using wide-band fluorescence. *Scientific Reports*, *6*, 23166. https://doi.org/10.1038/srep23166

Belongie, S., & Perona, P. (2016). Visipedia circa 2015. *Pattern Recognition Letters*, *72*, 15–24. https://doi.org/10.1016/j.patrec.2015.11.023

Berg, T., Liu, J., Lee, S. W., Alexander, M. L., Jacobs, D. W., & Belhumeur, P. N. (2014). Birdsnap: Large-scale fine-grained visual categorization of birds. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 2019–2026.

Berg, T. L., Sorokin, A., Forsyth, D. A., Hoiem, D., Endres, I., & Farhadi, A. (2010). It's all about the data. *Proceedings of the IEEE*, *98*, 1434–1452. https://doi.org/10.1109/JPROC.2009.2032355

Blanc, K., Lingrand, D., & Precioso, F. (2014). Fish species recognition from video using SVM classifier. *Proceedings of the 3rd ACM International Workshop on Multimedia Analysis for Ecological Data – MAED '14*, pp. 1–6. New York, NY: ACM Press. https://doi.org/10.1145/2661821

Bolger, D. T., Morrison, T. A., Vance, B., Lee, D., & Farid, H. (2012). A computer-assisted system for photographic mark-recapture analysis. *Methods in Ecology and Evolution*, *3*, 813–822. https://doi.org/10.1111/j.2041-210X.2012.00212.x

Bowley, C., Andes, A., Ellis-Felege, S., & Desell, T. (2017). Detecting wildlife in uncontrolled outdoor video using convolutional neural networks. *Proceedings of the 2016 IEEE 12th International Conference on e-Science, e-Science 2016*, pp. 251–259.

Bradski, G. (2000). The OpenCV Library. *Dr Dobbs Journal*, *25*, 120–126.

Branson, S., Van Horn, G., Belongie, S., & Perona, P. (2014). Bird species categorization using pose normalized deep convolutional nets.

British Machine Vision Conference (BMVC). http://www.bmva.org/bmvc/2014/files/paper071.pdf

Branson, S., Wah, C., Schroff, F., Babenko, B., Welinder, P., Perona, P., & Belongie, S. (2010). Visual recognition with humans in the loop. In Daniilidis K., Maragos P., Paragios N. (eds) *Computer Vision - ECCV 2010. ECCV 2010*. Lecture Notes in Computer Science, vol 6314. Berlin, Germany: Springer.

Chabot, D., & Francis, C. M. (2016). Computer-automated bird detection and counts in high-resolution aerial images: A review. *Journal of Field Ornithology*, *87*, 343–359. https://doi.org/10.1111/jofo.12171

Chen, G., Han, T. X., He, Z., Kays, R., & Forrester, T. (2014). Deep convolutional neural network based species recognition for wild animal monitoring. *IEEE International Conference on Image Processing (ICIP)*, *2014*, 858–862.

Christiansen, P., Nielsen, L., Steen, K., Jørgensen, R., & Karstoft, H. (2016). DeepAnomaly: Combining background subtraction and deep learning for detecting obstacles and anomalies in an agricultural field. *Sensors*, *16*, 1904. https://doi.org/10.3390/s16111904

Crall, J., Stewart, C., Berger-Wolf, T. Y., Rubenstein, D. L., & Sundaresan, S. R. (2013). Hotspotter – Patterned species instance recognition. *Applications of Computer Vision (WACV)*, *2013 IEEE Workshop*, pp. 230–237.

Cross, M. D., Lipps, G. J., Sapak, J. M., Tobin, E. J., & Root, K. V. (2014). Pattern-recognition software as a supplemental method of identifying individual eastern box turtles (*Terrapene c. carolina*). *Herpetological Review*, *45*, 584–586.

Crutsinger, G. M., Short, J., & Sollenberger, R. (2016). The future of UAVs in ecology: An insider perspective from the Silicon Valley drone industry. *Journal of Unmanned Vehicle Systems*, *4*, 161–168. https://doi.org/10.1139/juvs-2016-0008

Dala-Corte, R. B., Moschetta, J. B., & Becker, F. G. (2016). Photo-identification as a technique for recognition of individual fish: A test with the freshwater armored catfish *Rineloricaria aequalicuspis* Reis & Cardoso, 2001 (Siluriformes: Loricariidae). *Neotropical Ichthyology*, *14*, e150074.

Dell, A. I., Bender, J. A., Branson, K., Couzin, I. D., de Polavieja, G. G., Noldus, L. P. J. J., … Brose, U. (2014). Automated image-based tracking and its application in ecology. *Trends in Ecology and Evolution*, *29*, 417–428. https://doi.org/10.1016/j.tree.2014.05.004

Descamps, S., Béchet, A., Descombes, X., Arnaud, A., & Zerubia, J. (2011). An automatic counter for aerial images of aggregations of large birds. *Bird Study*, *58*, 302–308. https://doi.org/10.1080/00063657.2011.588195

Desell, T., Bergman, R., Goehner, K., Marsh, R., Vanderclute, R., & Ellis-Felege, S. (2013). Wildlife@Home: Combining crowd sourcing and volunteer computing to analyze avian nesting video. *Proceedings - IEEE 9th International Conference on e-Science, e-Science 2013*, pp. 107–115.

Duyck, J., Finn, C., Hutcheon, A., Vera, P., Salas, J., & Ravela, S. (2015). Sloop: A pattern retrieval engine for individual animal identification. *Pattern Recognition*, *48*, 1055–1069.

Farnsworth, E. J., Chu, M., Kress, W. J., Neill, A. K., Best, J. H., Stevenson, R. D., … Pickering, J. (2013). Next-generation field guides. *BioScience*, *63*, 891–899. https://doi.org/10.1525/bio.2013.63.11.8

Favret, C., & Sieracki, J. M. (2016). Machine vision automated species identification scaled towards production levels. *Systematic Entomology*, *41*, 133–143. https://doi.org/10.1111/syen.12146

Feng, L., Bhanu, B., & Heraty, J. (2016). A software system for automated identification and retrieval of moth images based on wing attributes. *Pattern Recognition*, *51*, 225–241. https://doi.org/10.1016/j.patcog.2015.09.012

Fretwell, P. T., Staniland, I. J., & Forcada, J. (2014). Whales from space: Counting southern right whales by satellite. *PLoS ONE*, *9*, 1–9. https://doi.org/10.1371/journal.pone.0088655

Gilman, A., Hupman, K., Stockin, K. A., & Pawley, M. D. M. (2016). Computer-assisted recognition of dolphin individuals using dorsal fin pigmentations. *2016 International Conference on Image and Vision Computing New Zealand (IVCNZ)*, 1-6.

Giraldo-Zuluaga, J.-H., Gomez, A., Salazar, A., & Diaz-Pulido, A. (2017). Camera-trap images segmentation using multi-layer robust principal component analysis. arXiv:1701.08180

Gomez, A., Diez, G., Salazar, A., & Diaz, A. (2016). Animal Identification in Low Quality Camera-Trap Images Using Very Deep Convolutional Neural Networks and Confidence Thresholds. *Advances in Visual Computing: 12th International Symposium, ISVC 2016, Las Vegas, NV, USA, December 12–14, 2016, Proceedings, Part I*, pp. 747–756. Springer International Publishing. https://doi.org/10.1007/978-3-319-50835-1

Groom, G., Krag Petersen, I., Anderson, M. D., & Fox, A. D. (2011). Using object-based analysis of image data to count birds: Mapping of Lesser Flamingos at Kamfers Dam, Northern Cape, South Africa. *International Journal of Remote Sensing*, *32*, 4611–4639. https://doi.org/10.1080/01431161.2010.489068

Haggag, H., Abobakr, A., Hossny, M., & Nahavandi, S. (2016). Semantic body parts segmentation for quadrupedal animals. *2016 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 855–860.

Hernández-Serna, A., & Jiménez-Segura, L. F. (2014). Automatic identification of species with neural networks. *PeerJ*, *2*, e563. https://doi.org/10.7717/peerj.563

Hodgson, A., Kelly, N., & Peel, D. (2013). Unmanned aerial vehicles (UAVs) for surveying Marine Fauna: A dugong case study. *PLoS ONE*, *8*, 1–15.

Howland, J. C., Macfarlane, N. B. W., & Tyack, P. (2012). Precise geopositioning of marine mammals using stereo photogrammetry. *OCEANS 2012 MTS/IEEE: Harnessing the Power of the Ocean*. pp. 1-6. https://doi.org/10.1109/OCEANS.2012.6404859.

Joly, A., Goëau, H., Bonnet, P., Bakić, V., Barbe, J., Selmi, S., … Barthélémy, D. (2014). Interactive plant identification based on social image data. *Ecological Informatics*, *23*, 22–34. https://doi.org/10.1016/j.ecoinf.2013.07.006

Jones, A. M., Cantin, N. E., Berkelmans, R., Sinclair, B., & Negri, A. P. (2008). A 3D modeling method to calculate the surface areas of coral branches. *Coral Reefs*, *27*, 521–526. https://doi.org/10.1007/s00338-008-0354-y

Kosmala, M., Crall, A., Cheng, R., Hufkens, K., Henderson, S., & Richardson, A. (2016). Season spotter: Using citizen science to validate and scale plant phenology from near-surface remote sensing. *Remote Sensing*, *8*, 726. https://doi.org/10.3390/rs8090726

Kühl, H. S., & Burghardt, T. (2013). Animal biometrics: Quantifying and detecting phenotypic appearance. *Trends in Ecology and Evolution*, *28*, 432–441. https://doi.org/10.1016/j.tree.2013.02.013

Kvilekval, K., Fedorov, D., Obara, B., Singh, A., & Manjunath, B. S. (2009). Bisque: A platform for bioimage analysis and management. *Bioinformatics*, *26*, 544–552. https://doi.org/10.1093/bioinformatics/btp699

LaRue, M. A., Stapleton, S., & Anderson, M. (2016). Feasibility of using high-resolution satellite imagery to assess vertebrate wildlife populations. *Conservation Biology*, *31*, 213–220. https://doi.org/10.1111/cobi.12809

LaRue, M. A., Stapleton, S., Porter, C., Atkinson, S., Atwood, T., Dyck, M., & Lecomte, N. (2015). Testing methods for using high-resolution satellite imagery to monitor polar bear abundance and distribution. *Wildlife Society Bulletin*, *39*, 772–779. https://doi.org/10.1002/wsb.596

Lavy, A., Eyal, G., Neal, B., Keren, R., Loya, Y., & Ilan, M. (2015). A quick, easy and non-intrusive method for underwater volume and surface area evaluation of benthic organisms by 3D computer modelling. *Methods in Ecology and Evolution*, *6*, 521–531. https://doi.org/10.1111/2041-210X.12331

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*, 436–444. https://doi.org/10.1038/nature14539

Levy, K., Lerner, A., & Shashar, N. (2014). Mate choice and body pattern variations in the Crown Butterfly fish *Chaetodon paucifasciatus* (Chaetodontidae). *Biology Open*, *3*, 1245–1251. https://doi.org/10.1242/bio.20149175

Liu, C. C., Chen, Y. H., & Wen, H. L. (2015). Supporting the annual international black-faced spoonbill census with a low-cost unmanned aerial vehicle. *Ecological Informatics*, *30*, 170–178. https://doi.org/10.1016/j.ecoinf.2015.10.008

Lynch, H. J., White, R., Black, A. D., & Naveen, R. (2012). Detection, differentiation, and abundance estimation of penguin species by high-resolution satellite imagery. *Polar Biology*, *35*, 963–968. https://doi.org/10.1007/s00300-011-1138-3

Lytle, D. A., Martínez-Muñoz, G., Zhang, W., Larios, N., Shapiro, L., Paasch, R., … Dietterich, T. G. (2010). Automated processing and identification of benthic invertebrate samples. *Journal of the North American Benthological Society*, *29*, 867–874. https://doi.org/10.1899/09-080.1

Marburg, A., & Bigham, K. (2016). *Deep learning for benthic fauna identification*. OCEANS 2016 MTS/IEEE Monterey, pp. 1–5.

Matuska, S., Hudec, R., Kamencay, P., Benco, M., & Zachariasova, M. (2014). Classification of wild animals based on SVM and local descriptors. *AASRI Procedia*, *9*, 25–30. https://doi.org/10.1016/j.aasri.2014.09.006

McDowall, P., & Lynch, H. J. (2017). Ultra-fine scale spatially-integrated mapping of habitat and occupancy using structure. *PLoS ONE*, *12*, 1–16. https://doi.org/10.1371/journal.pone.0166773

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, *7*, 1–7. https://doi.org/10.3389/fpls.2016.01419

Naumann, M. S., Niggl, W., Laforsch, C., Glaser, C., & Wild, C. (2009). Coral surface area quantification-evaluation of established techniques by comparison with computer tomography. *Coral Reefs*, *28*, 109–117. https://doi.org/10.1007/s00338-008-0459-3

Olsen, A. M., & Westneat, M. W. (2015). StereoMorph: An R package for the collection of 3D landmarks and curves using a stereo camera set-up. *Methods in Ecology and Evolution*, *6*, 351–356. https://doi.org/10.1111/2041-210X.12326

Pennekamp, F., & Schtickzelle, N. (2013). Implementing image analysis in laboratory-based experimental systems for ecology and evolution: A hands-on guide. *Methods in Ecology and Evolution*, *4*, 483–492. https://doi.org/10.1111/2041-210X.12036

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

Price Tack, J. L., West, B. S., McGowan, C. P., Ditchkoff, S. S., Reeves, S. J., Keever, A. C., & Grand, J. B. (2016). AnimalFinder: A semi-automated system for animal detection in time-lapse camera trap images. *Ecological Informatics*, *36*, 145–151. https://doi.org/10.1016/j.ecoinf.2016.11.003

Qin, H., Li, X., Liang, J., Peng, Y., & Zhang, C. (2016). DeepFish: Accurate underwater live fish recognition with a deep architecture. *Neurocomputing*, *187*, 49–58. https://doi.org/10.1016/j.neucom.2015.10.122

Reda, K., Mateevitsi, V., & Offord, C. (2013). A human-computer collaborative workflow for the acquisition and analysis of terrestrial insect movement in behavioral field studies. *EURASIP Journal on Image and Video Processing*, *2013*, 48. https://doi.org/10.1186/1687-5281-2013-48

Ren, X., Han, T. X., & He, Z. (2013). Ensemble video object cut in highly dynamic scenes. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 1947–1954.

Robie, A. A., Seagraves, K. M., Egnor, S. E. R., & Branson, K. (2017). Machine vision methods for analyzing social interactions. *The Journal of Experimental Biology*, *220*, 25–34. https://doi.org/10.1242/jeb.142281

Seymour, A. C., Dale, J., Hammill, M., Halpin, P. N., & Johnston, D. W. (2017). Automated detection and enumeration of marine wildlife using unmanned aircraft systems (UAS) and thermal imagery. *Scientific Reports*, *7*, 1–10. https://doi.org/10.1038/srep45127

Sobral, A., & Vacavant, A. (2014). A comprehensive review of background subtraction algorithms evaluated with synthetic and real videos. *Computer Vision and Image Understanding*, *122*, 4–21. https://doi.org/10.1016/j.cviu.2013.12.005

Stauffer, C., & Grimson, W. E. L. (1999). *Adaptive background mixture models for real-time tracking*. Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 246–252. IEEE Comput. Soc.

Steen, R., & Ski, S. (2014). Video-surveillance system for remote long-term in situ observations: Recording diel cavity use and behaviour of wild European lobsters (*Homarus gammarus*). *Marine and Freshwater Research*, *65*, 1094–1101. https://doi.org/10.1071/MF13139

Stoddard, M. C., Kilner, R. M., & Town, C. (2014). Pattern recognition algorithm reveals how birds evolve individual egg pattern signatures. *Nature Communications*, *5*, 4117.

Stoddard, M. C., Kupán, K., Eyster, H. N., Rojas-Abreu, W., Cruz-López, M., Serrano-Meneses, M. A., & Küpper, C. (2016). Camouflage and clutch survival in plovers and terns. *Scientific Reports*, *6*, 32059. https://doi.org/10.1038/srep32059

Sun, X., Shi, J., Dong, J., & Wang, X. (2017). Fish recognition from low-resolution underwater images. In *Proceedings of the 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics*, CISP-BMEI 2016, pp. 471–476.

Swanson, A., Kosmala, M., Lintott, C., & Packer, C. (2016). A generalized approach for producing, quantifying, and validating citizen science data from wildlife images. *Conservation Biology*, *30*, 520–531. https://doi.org/10.1111/cobi.12695

Swanson, A., Kosmala, M., Lintott, C., Simpson, R., Smith, A., & Packer, C. (2015). Snapshot Serengeti, high-frequency annotated camera trap images of 40 mammalian species in an African savanna. *Scientific Data*, *2*, 150026. https://doi.org/10.1038/sdata.2015.26

Tankus, A., & Yeshurun, Y. (2009). Computer vision, camouflage breaking and countershading. *Philosophical Transactions of the Royal Society of London Series B, Biological Sciences*, *364*, 529–536. https://doi.org/10.1098/rstb.2008.0211

Torney, C. J., Dobson, A. P., Borner, F., Lloyd-Jones, D. J., Moyer, D., Maliti, H. T., … Hopcraft, J. G. C. (2016). Assessing rotation-invariant feature classification for automated wildebeest population counts. *PLoS ONE*, *11*, e0156342. https://doi.org/10.1371/journal.pone.0156342

Town, C., Marshall, A., & Sethasathien, N. (2013). Manta matcher: Automated photographic identification of manta rays using keypoint features. *Ecology and Evolution*, *3*, 1902–1914. https://doi.org/10.1002/ece3.587

Troscianko, J., Skelhorn, J., & Stevens, M. (2017). Quantifying camouflage: How to predict detectability from appearance. *BMC Evolutionary Biology*, *17*, 7. https://doi.org/10.1186/s12862-016-0854-2

van Andel, A. C., Wich, S. A., Boesch, C., Koh, L. P., Robbins, M. M., Kelly, J., & Kuehl, H. S. (2015). Locating chimpanzee nests and identifying fruiting trees with an unmanned aerial vehicle. *American Journal of Primatology*, *77*, 1122–1134. https://doi.org/10.1002/ajp.22446

Van Horn, G., Branson, S., Farrell, R., Haber, S., Barry, J., Ipeirotis, P., … Belongie, S. (2015). Building a bird recognition app and large scale dataset with citizen scientists: The fine print in fine-grained dataset collection. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 595–604.

Van Horn, G., Mac Aodha, O., Song, Y., Shepard, A., Adam, H., Perona, P., & Belongie, S. (2017). The iNaturalist Challenge 2017 Dataset. arXiv preprint arXiv:1707.06642.

Villon, S., Chaumont, M., Subsol, G., Villéger, S., Claverie, T., & Mouillot, D. (2016). Coral reef fish detection and recognition in underwater videos by supervised machine learning: Comparison between deep learning and HOG+SVM methods. In Blanc-Talon J., Distante C., Philips W., Popescu D., Scheunders P. (eds) *Advanced Concepts for Intelligent Vision Systems. ACIVS 2016*. Lecture Notes in Computer Science, vol 10016. Cham, Switzerland: Springer.

Weinstein, B. G. (2015). MotionMeerkat: Integrating motion video detection and ecological monitoring. *Methods in Ecology and Evolution*, *6*, 357–362. https://doi.org/10.1111/2041-210X.12320

Weinstein, B. G. (2017). Data from: A computer vision for animal ecology. *Dryad Digital Repository*, https://doi.org/10.5061/dryad.b700h

Weinstein, B. G., & Graham, C. H. (2017). Persistent bill and corolla matching despite shifting temporal resources in tropical hummingbird-plant interactions. *Ecology Letters*, *20*, 326–335. https://doi.org/10.1111/ele.12730

Wilber, M. J., Scheirer, W. J., Leitner, P., Heflin, B., Zott, J., Reinke, D., … Boult, T. E. (2013). Animal recognition in the Mojave Desert: Vision tools for field biologists. *2013 IEEE Workshop on Applications of Computer Vision (WACV)*, pp. 206–213.

Witharana, C., & Lynch, H. J. (2016). An object-based image analysis approach for detecting penguin guano in very high spatial resolution satellite images. *Remote Sensing*, *8*, 375. https://doi.org/10.3390/rs8050375

Yang, C., Wang, L., Liang, W., & Møller, A. P. (2016). Do common cuckoos (*Cuculus canorus*) possess an optimal laying behaviour to match their own egg phenotype to that of their Oriental reed warbler (*Acrocephalus orientalis*) hosts? *Biological Journal of the Linnean Society*, *117*, 422–427. https://doi.org/10.1111/bij.12690

Yang, Z., Wang, T., Skidmore, A. K., De Leeuw, J., Said, M. Y., & Freer, J. (2014). Spotting East African mammals in open savannah from space. *PLoS ONE*, *9*, 1–16.

Yu, X., Wang, J., Kays, R., Jansen, P. A., Wang, T., & Huang, T. (2013). Automated identification of animal species in camera trap images. *EURASIP Journal on Image and Video Processing*, *2013*, 52. https://doi.org/10.1186/1687-5281-2013-52

Zeppelzauer, M. (2013). Automated detection of elephants in wildlife video. *EURASIP Journal on Image and Video Processing*, *2013*, 46. https://doi.org/10.1186/1687-5281-2013-46

Zhang, Z., He, Z., Cao, G., & Cao, W. (2016). Animal detection from highly cluttered natural scenes using spatiotemporal object region proposals and patch verification. *IEEE Transactions on Multimedia*, *18*, 2079–2092. https://doi.org/10.1109/TMM.2016.2594138

Zhang, H., Korayem, M., Crandall, D. J., & Lebuhn, G. (2012). *Mining Photo-sharing Websites to Study Ecological Phenomena*. International World Wide Web Conference Committee (IW3C2), pp. 749–758.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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