**Title**: The use of photos to investigate ecological change

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All authors contributed to the concept and design of the article. LD prepared the manuscript with input from PDF and HB for the introduction, HB, KDP and PDF for the literature review, PV, EDL, TV, KDP, EL and KV for the case studies, and DL and EL for the chapter on future perspectives and for box 2. HB, PV, KDP and LD created the figures for the article. All authors reviewed the final version of the manuscript.

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**Abstract**

1. Global change is causing ecosystems to change at unprecedented rates and the urgency to quantify ecological change is high. We therefore need all possible sources of ecological data to address key knowledge gaps.
2. Ground-based photos are a form of remote sensing and an unconventional data source with a high potential to improve our understanding of ecological change. They can provide invaluable information on ecological conditions in the past and present at relevant spatiotemporal scales that is very difficult to obtain with other approaches.
3. Here we review the use of ground-based photos in a set of relevant ecological research topics, such as biodiversity and community ecology, phenology, global change ecology and landscape ecology. We highlight three main photo-based methods in ecological research (repeat photography, time-lapse photography and public archives), alongside which we discuss three case studies to demonstrate novel applications of these methods, to answer fundamental ecological questions.
4. *Synthesis:* Photos can significantly support ecological research to improve our understanding of biotic responses in a rapidly changing world. Photos cover relatively large temporal and spatial scales, and can provide large amounts of information with limited time investment. To exploit their full potential, we need to invest not only in technological advances to compile, process and analyze images but also in proper data management.

## Introduction

Ecosystems across the globe are changing at unprecedented rates owing to global-change drivers such as climate change, land-use change, invasive species, and enhanced inputs of nutrients and other pollutants (Komatsu et al., 2019). Biodiversity and community composition in numerous ecosystems across the globe are strongly influenced by eutrophication and climate change (Hautier et al., 2020; Staude et al., 2020; Zellweger et al., 2020). Furthering our mechanistic understanding and predicting the future impacts of global change is one of the key aims of ecology, as the rate of current change, and its impacts on ecosystems and human well-being, is high (Büntgen et al., 2021; Pecl et al., 2017). Therefore, we need all possible sources of data to quantify ecological changes and address key knowledge gaps.

Photos are an often-overlooked source of data in ecology, although they have occasionally served as a data source in several research fields in ecology, such as landscape ecology (e.g. to track long-term land cover changes (Danby & Hik, 2007; Harsch et al., 2009)), wildlife ecology (e.g. nesting behaviour and feeding ecology; see Cutler & Swann (1999) for a review), and species distribution monitoring of both animals (e.g. Rousselet et al., 2013) and plants (e.g. Dyrmann et al., 2021; Kotowska et al., 2021). Photos are a type of legacy remote sensing data that allow scientists to test for global environmental change effects (*sensu* Vellend et al., 2013), just as herbarium specimens, resurveyed vegetation plots and land survey records (De Frenne, 2015; reviewed by Vellend et al., 2013; Willis et al., 2017). They can provide additional, complementary and novel insights that are not possible to achieve with other data types. Moreover, their use can be more time- and cost-effective than traditional research methods for many applications. With rapid ongoing advances in digital photography, and the ubiquity of (phone) cameras in our daily life, the availability of image data is growing exponentially. However, their use in ecological change studies remains a marginal phenomenon, rather than a structurally recognized source of data.

Many ecological processes are impossible to fully understand without considering changes over longer time spans of several years, decades, and even centuries. Quantifying such long-term patterns is particularly challenging with conventional scientific methods, especially because research projects typically span shorter time periods (< 5 years). Local environmental knowledge, passed on from one generation to another, is susceptible to the inaccurate human perception of ecosystem changes (‘shifting baseline syndrome’; see Fernández-Llamazares et al., 2015; Pauly, 1995). Even the famous work of Alexander von Humboldt, the *Tableau Physique* (1807) of Mt. Chimborazo in Ecuador depicting zones of distinct vegetation types, often used as a baseline to track altitudinal vegetation shifts (e.g. Morueta-Holme et al., 2015), is known to contain partly false field data (Hestmark, 2019; Moret et al., 2019). Historical photos on the other hand, can provide unbiased evidence of past conditions. Therefore, we focus our review on the use of time series of ground-based historical photographs of species, ecosystems and landscapes to monitor, understand and evaluate temporal ecological change at timescales spanning at least several weeks. In particular, we see most interesting applications in the following research areas: global change ecology, community and biodiversity ecology, phenology, landscape ecology, invasion ecology, human (disturbance) and urban ecology, and agroecology (these were selected from the list of focal topics of the British Ecological Society, see **SI Appendix S1** for more information on our selection procedure based on expert knowledge).

We limit our study to photos meeting the following criteria: “a ground-based image (photograph) produced by a colour/monochrome camera, from distances in the range 0.1 m - 100 m, with known location and time”. We focus on ground-based monochrome (black & white: BW) and colour (red, green, blue: RGB) photographs as particularly interesting, given their two-century long history, which makes them ideally suited to study ecological changes through time. Indeed, significantly older images are available compared to more recent techniques such as thermal, multispectral and hyperspectral imaging and laser scanning via light detection and ranging (LiDAR).

Ground-based photos also clearly complement airborne and satellite remote sensing, and have the potential to offer additional insights in terms of spatial resolution and temporal extent of the data (Vellend et al., 2013). The oldest satellite image of the earth surface was made in 1959 (by the US Explorer) and the oldest continuous satellite imagery is from the Landsat program, which has been collecting images at 30 m resolution since the 1980s. The first airborne photos (e.g., orthophotos) are, depending on the country, available since the World Wars. Archived ground-based photos, on the other hand, have the potential to go significantly farther back in time than a century for ecological research (Lanckriet et al., 2015; Pickard, 2002; Rohde & Hoffman, 2012). In a recent study on Greenland's glacial cap, the researchers note that "… *collecting historical data sets is probably more important at this point than having yet another satellite do more of the same stuff…*" (Schiermeier, 2016). In terms of spatial resolution, contemporary satellite and airborne images are perfectly appropriate to track e.g. tree leafing phenology and tree line shifts across open landscapes (Mohapatra et al., 2019), but they are often not suitable to track flowering phenology of herbaceous vegetation, range shifts of individual plants, or in forests where below-canopy biodiversity is not visible from above the canopy. Ground-based photography is thus often able to provide more accurate and long-term information of spatial and temporal vegetation change compared to remote sensing data (Fitzgerald et al., 2021).

The overarching aim of this review is to demonstrate the high potential of photographs in ecological change research as a data source, to provide insights that could not have been generated in any other way, or as an alternative to more expensive and time-consuming data collection methods. We highlight three promising avenues for the use of photos to study changes in plant ecology: repeat photography, time-lapse photography and public archives (**Figure 1**). For each approach, we first discuss how they are currently used to quantify ecological change. Next, we present a fitting case study in which we demonstrate the potential of each approach to answer key questions and fill important research gaps in ecological change, and propose innovative research directions to strengthen the approaches. Finally, we discuss possible scientific and technical advances that can further boost the potential of photographs for studying ecological change in the future.

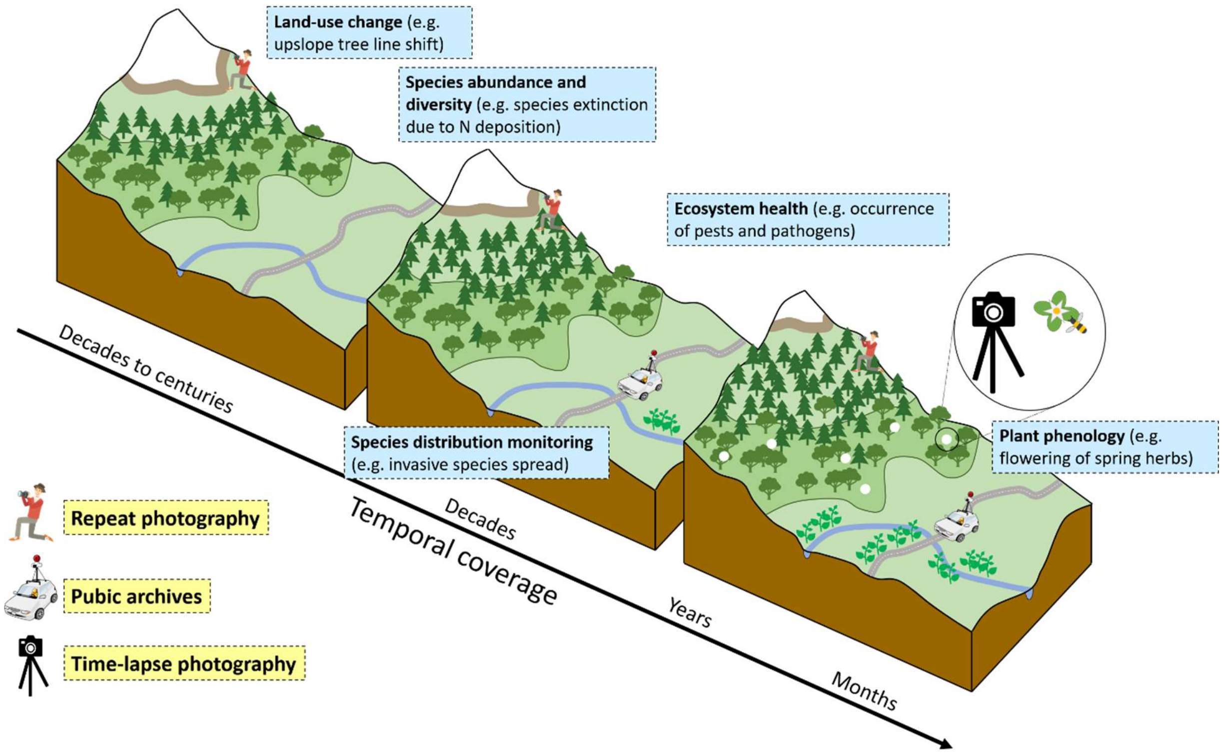


**Figure 1. Conceptual figure illustrating how three different photography approaches can provide ecological knowledge at different spatial and temporal scales**. The yellow boxes indicate the three approaches. The blue boxes indicate the knowledge that can be obtained. The position along the 'temporal coverage' axis provides a (very rough) indication of the time scale at which these types of knowledge are typically assessed. Repeat photography (replicating pre-existing photos) is particularly valuable to assess long-term (decades to centuries) ecological changes at the landscape scale, such as land-use changes. Public archives such as Google Street View typically have a lower temporal coverage (decades), but a potentially very high spatial coverage (virtually global), and can for instance be used to monitor species distribution. Time-lapse photographs have a low temporal coverage (e.g. one-year study) but a high temporal resolution (e.g. every second/hour/day), and a varying spatial cover and

resolution (depending on the research questions). They can, for instance, provide valuable data on plant phenology and pollination.

## Three promising avenues for the use of photos in ecological change research

To quantify the relative contribution of photography as a data source for ecological studies, we performed a systematic literature search. First, we selected eleven topics (listed in **Fig. 2**) from the journals of the British Ecological Society's (BES, https://besjournals.onlinelibrary.wiley.com/) research topics list, for which we expected photographs to be a promising data source. Therefore, eight co-authors of this paper scored each topic, based on the following question: 'How high do you estimate the usefulness/potential of photographs as a data source to address the following research topics?' (the full selection procedure is described in **SI Appendix S1**). Then, we searched the literature for each topic, with and without a set of search terms specifically related to photography (see **SI Appendix S2** for search strings per topic). The list of papers related to photography was further reduced through manual screening of their titles and abstracts. Overall, the share of the literature that made use of ground-based photographs as a data source was low for all topics (1.24 % for 'phenology', 0.30 % for 'global change ecology' and < 0.20 % for all other topics; **SI Appendix S2**). Across all selected topics, we found 206 papers using photos as a data source, from which several belonged to two or more topics (**SI Appendix S2**).

Based on this literature search, we identified three key methodological approaches that have a high potential to improve our understanding of ecological change, and provide insights that go beyond what can be reached with more conventional methods. The three approaches are repeat photography (replicating pre-existing photos), time-lapse photography (fixed on-site camera taking photos at specified time intervals), and public archives (e.g. Google Street View, television footage, traffic or CCTV cameras). In **Fig. 2**, we visualize the relative contribution of these three approaches in the retained publications, and their relative importance per research topic.

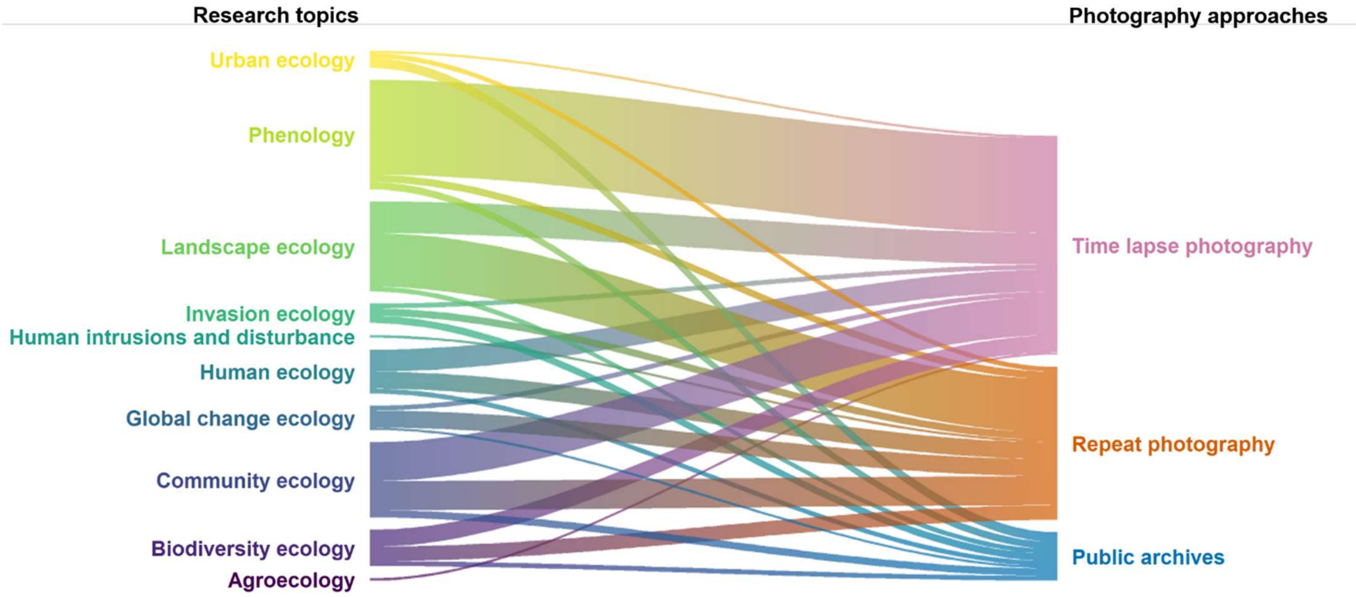


**Figure 2. Visualization of the relative contribution of the three main photography approaches (on the right) for each research topic (on the left).** The width of each link between nodes quantifies the number of publications found for a specific topic, using a specific approach.

Each of these three approaches has specific features that determine their suitability for specific research goals in ecology. We developed an evaluation framework to enable appropriate selection of photography methods to study ecological change, depending on the goal of the study (e.g. reveal land-use changes or phenology shifts), on the spatial scale (e.g. global or local) and on the availability of resources in the study region (e.g. photos from public archives available?). We based our evaluation framework on eight criteria for monitoring ecological change, which are described in **Box 1**. The full evaluation of the three approaches is given in **SI Appendix 3**, and a summary is shown in **Fig. 3**. Below, for each approach, we first provide insight in their key characteristics, with reference to the established evaluation criteria, and discuss their current applications in ecology. Then, we present a case study to demonstrate their potential to fill important research gaps in ecological change, and propose innovative research directions that can further strengthen the approach. Below, we mainly focus on the specific properties, opportunities, challenges and new potential research directions for each approach, and less on the technical aspects of image analysis. In **Box 2**, we provide an overarching comprehensive overview of the workflow that can be followed when analyzing images derived from any of the three approaches, to obtain quantitative data.

**Box 1: eight criteria for monitoring ecological change**

The first four criteria (Magurran et al., 2010; Verburg et al., 2011) describe the temporal and spatial scale of the research: **temporal coverage** refers to the time between the first and the last moment of data collection, while **temporal resolution** refers to the frequency of data collection events. Similarly, **spatial coverage** refers to the geographical limits of the overall area of data collection, while **spatial resolution** refers to the distance between data collection points (i.e. the number of data collection points per unit surface area). In addition, a **consistent methodology** (across space and time) is crucial to allow data comparisons (Borer et al., 2014; Magurran et al., 2010), and **versatility** ensures the applicability of a method in a wide array of study types (De Frenne, 2015). **Resource-effectiveness** (both in terms of financial costs and time investment) is often an important criterion to choose an appropriate and feasible methodology (Pieter De Frenne, 2015; Spellerberg, 2005). Finally, the **environmental impact** of the methods should be considered too, and preferably kept to a minimum (Spellerberg, 2005).

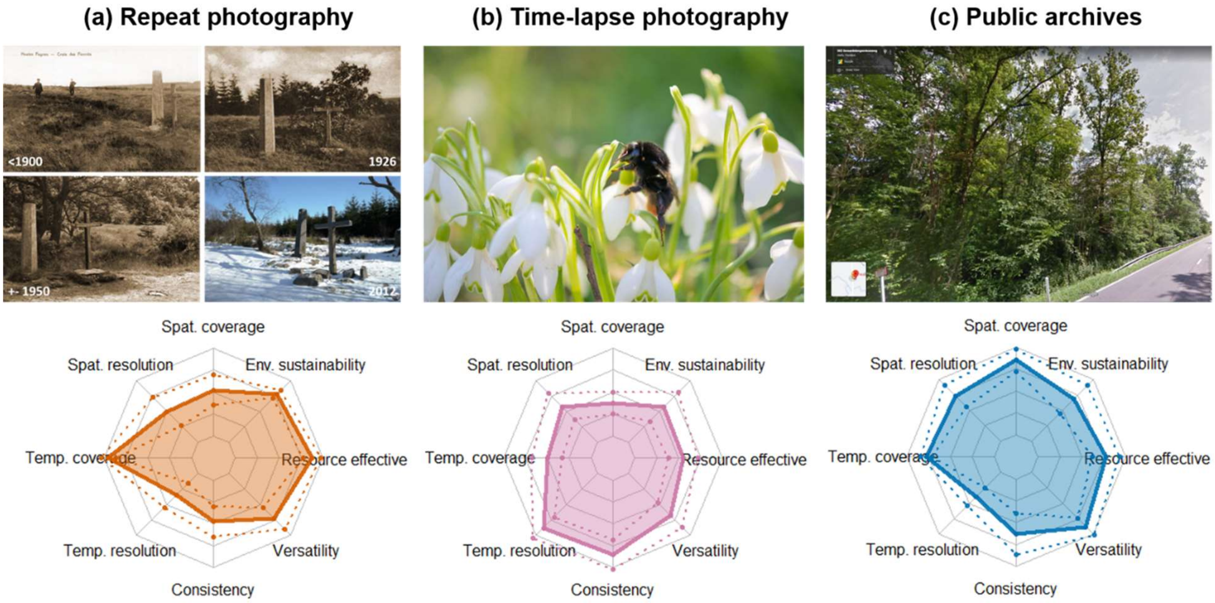


**Figure 3. Evaluation of the three photography methods, along eight criteria (described in Box 1):** spatial coverage, spatial resolution, temporal coverage, temporal resolution, methodological consistency, versatility, resource-effectiveness and environmental sustainability. The axes are scaled from 1 (very low) to 5 (very good), and scores were obtained using an incremental scoring system and averaged across eight authors of this paper. The dotted lines indicate the standard deviation of the scores. Potential challenges and opportunities to meet the criteria are described in **SI Appendix 3**. The photos refer to the case study for each method: (a) Repeat photography with crowdsourced pictures of landmarks can be used to investigate long term landscape changes (example of Croix des Fiancés, Belgium). Photos restored by Jean-Marie Siebertz (http://gite-ardennais.com/croixdesfiances.html); (b) Time-lapse cameras can be used to monitor possible mismatches between flowering time of spring geophytes (*Galanthus nivalis*) and pollinators (*Bombus lapidarius*) in forests with contrasting microclimates ((c) Robin Bosteels); (c) Google Street View can be used to study plant species distribution.

Repeat photography

Repeat photography is the practice of replicating pre-existing photographs in the field, to enable comparisons over time and reconstruct change. It is a common method to analyze long-term landscape, land-use and vegetation changes from an ecological perspective (Nusser, 2000; Pickard, 2002; Santana-Cordero & Szabo, 2019; Vellend et al., 2013). Repeat photos allow researchers to study the effect of anthropogenic and natural disturbances on a finer spatial resolution than is possible with satellite imagery (Hammond et al., 2020), and at timescales beyond those accessible by long-term ecological monitoring (Hoffman et al., 2020). They allow to obtain insights in historical ecological conditions with limited resources.

Historical photographs can be retaken at the same location today and used to look back in time (Poulsen & Hoffman, 2015; Sanseverino et al., 2016), even as far as 1868 (Lanckriet et al., 2015), to assess e.g. forest cover change (Lanckriet et al., 2015; Zier & Baker, 2006), change in grass- and shrubland (Masubelele et al., 2015; Rinas et al., 2017), change in use and/or abandonment of agricultural land (Hoffman & Rohde, 2007; Shackleton et al., 2019), change in shrub and tree distribution in boreal Alaska (Brodie et al., 2019), and vegetation shifts to higher elevations (Konchar et al., 2015). Historical photographs were initially often not taken for scientific purposes. For example, Eufracio-Torres et al. (2016) used private family pictures dating back to 1925 to study vegetation changes along river banks. Repeat photography is also used on smaller time scales compared to repeat historical photographs, when new time-series are started by researchers who frequently (e.g. once a year) revisit the study site(s) (Hammond et al., 2020). For instance, (Hietz et al., 2002) used repeated photographs of branches, taken once a year in summer, to monitor the growth and survival of epiphytes over a five-year period.

Repeat photography typically requires image preprocessing (e.g. feature matching or resolution matching) to enable a direct comparison of the ecological features of interest (see **Box 2**). After pictures are matched, the images can be analyzed with different approaches depending on the question. Forest structure and structural complexity can be derived from close-range repeat photography and mathematical tools (such as recurrence plots and recurrence quantification analysis) (Proulx & Parrott, 2009), but more and more types of analyses are advancing through machine learning. Landscape changes in forest cover or other land-use types are currently still mainly obtained through manual categorization (e.g. Fortin et al., 2019; Stockdale et al., 2019), whereas these could be assigned automatically through texture analysis and classic machine learning techniques (Jean et al., 2015) or deep learning (Bayr & Puschmann, 2019). Furthermore, the vitality and defoliation of single trees can be estimated via neural networks (Kälin et al., 2019) and many more applications will undoubtedly follow.

*Case study: active crowdsourcing of photographs to increase the temporal coverage and resolution of repeat photography*

Internet-based crowdsourcing of photographs has the potential to further increase the strengths of repeat photography. Typically, historic photographs found in libraries, archives, public collections, etc. are used to study ecological change (e.g. Eufracio-Torres et al., 2016). However, these pictures probably cover only a tiny fraction of the zillions of pictures that were taken during excursions, family walks, etc. and that are now stored in old photo books or boxes in people's private archives. Until recently it was virtually impossible to access these pictures, but internet-based platforms and social media now allow crowdsourcing these valuable sources of information (Marcenò et al., 2021; See et al., 2016). For instance, one could think of a web-based platform, advertised via social media and in the field via fixed "poles" (e.g. with a QR code), on which people can upload their scanned old or new pictures of an area or location under study and also enter relevant metadata (geographic location, date and time of the day, etc.). This approach is called *active* crowdsourcing, and depends on users actively contributing with data through online platforms specifically designed to collect data about users or nature qualities (Muñoz et al., 2020). Active crowdsourcing is increasingly being used in the field of cultural ecosystem services, e.g. to identify preferred locations within the landscape (Ridding et al., 2018), but this approach could be extended to other research fields, and include the active sharing of georeferenced image data. An emerging tool for active crowdsourcing is public participatory geographic information systems (PPGIS), which are online mapping platforms where participants can enter specific georeferenced data (Brown & Kyttä, 2014). Such an approach would allow us to further extend the temporal coverage and resolution of repeat photographs and extend their spatial coverage and resolution. Well-known landmarks would be ideally suited to extend time series of repeated photographs through crowdsourcing, as they are popular destinations for hikers, easy to recognize and georeference, and historical photographs often exist. For instance, in the High Fens (a Belgian nature reserve), *La Croix des Fiancés* is a famous cross placed in memory of a young couple who lost their lives in a blizzard in 1871. Many historical photographs of this place exist (e.g. https://gite-ardennais.com/croixdesfiances.html; see **Fig. 2**), and the famous cross is still a popular destination for hikers nowadays. An information sign on the spot could inform visitors about the platform where they can upload old pictures, and/or ask visitors to take a picture of the cross and surrounding landscape and upload it immediately. Such initiatives could result in datasets with an exceptionally high temporal coverage and increased temporal resolution from crowdsourced historic photographs, while continuing this at present with immediate uploads of newly taken pictures. Such a dataset could be used to study temporal changes on the landscape scale, for instance, changes in forest cover, but also local changes in plant community composition, vegetation complexity or phenology of individual trees. Although citizens are becoming an increasingly important source of geographic information (e.g. See et al., 2016), we are unaware of a study that applied this promising approach to study ecological change.

Time-lapse photography

Time-lapse photography, also called continuous photography, is obtained through a fixed camera (left in place on-site) that takes photos at specified time intervals (typically ranging from several seconds to days). Time-lapse images and continuous image recording techniques have been shown to document ecological changes from periods ranging from weeks (Xu et al., 2021), years (Yanoviak et al., 2017) to decennia (Kankaanpaa et al., 2018). Time-lapse photography typically has a lower temporal coverage, but a much higher temporal resolution than repeat photography. As the camera is typically fixed, it allows a very consistent comparison of images through time. Time-lapse photography can be resource intensive, depending on the number of sites where data are collected, and the number of field visits required. The recent advances in remote data transfer technologies (see case study) can improve resource effectiveness.

Time-lapse photography is regularly used in the study of vegetation phenology, especially in relation to climate change. “Near-surface” remote sensing, for instance based on a network of digital cameras (“webcams”), has great potential to improve phenological monitoring. For instance, Richardson et al. (2009) used images from networked webcams to assess spatial and temporal variation in canopy phenology. Also, many networks of so-called ‘phenocams’ were started during the last decade to build databases of images to assess phenological change over larger spatial scales (Brown et al., 2016; Mariano et al., 2016; Nasahara & Nagai, 2015; Osenga et al., 2019; Seyednasrollah et al., 2019; Tang et al., 2016; Thorpe et al., 2016).

Besides phenology, especially pollination is assessed through time-lapse cameras or videos (Balfour & Ratnieks, 2017; Bonelli et al., 2020; Gilpin et al., 2017; Ladd & Arroyo, 2009; Ratnayake et al., 2021), for instance to count the number of pollinator visits (Sakata et al., 2014) or to detect changes in foraging strategies (Paolo Biella et al., 2019). Furthermore, there are examples of the use of time-lapse photography to assess pest predation in agricultural fields (Zou et al., 2017), browsing of specific plant species (Ecroyd, 1996) and foraging on plants by hummingbirds (Biella et al., 2019). Hall et al. (2020) monitored foraging behaviour of sheep in species-rich grasslands through installing time-lapse cameras on the sheep themselves.

Even more than for repeat photography, the number of unique images that need to be screened or analyzed can add up quickly, easily reaching $10^4$ - $10^6$ even when operated on relatively short terms (e.g. one image taken every hour for three months at ten sites results in 21,600 photos). To reduce time investments, there is a growing need for software for automated image recognition (e.g. AnimalFinder (Price Tack et al., 2016), MotionMeerkat (Weinstein, 2015)) or data extraction (e.g. Correia et al., 2020; Filippa et al., 2016; Proulx & Parrott, 2009) (see **Box 2**). This is clearly an emerging field and exciting new developments are made. For instance, Høye et al. (2021) monitored flower-visiting insects with camera traps and used deep learning models to identify species. In addition, citizen science platforms can assist in rapidly processing large image datasets (Jones et al., 2020; Kosmala et al., 2016).

*Case study: combining time-lapse photography with remote data transfer technologies to study phenology and pollination*

An outstanding question in ecology is to what extent climate change will influence trophic interactions due to phenological change (Sutherland et al., 2013). For instance, warming temperatures could lead to advanced flowering of forest spring ephemerals (Petrauski et al., 2019), but this effect will be strongly mediated by local microclimate, e.g. with stronger effects in open forests or on south-oriented slopes. These differences in flowering time potentially have strong feedbacks on associated pollinator communities (Gezon et al., 2016; Kudo & Cooper, 2019). Recent techniques such as time-lapse photography, video monitoring and camera traps are excellently suited to help bridge this knowledge gap. Indeed, many studies already use digital time-lapse cameras to evaluate phenology and data from these so-called *Phenocam* networks is made publicly available (Seyednasrollah et al., 2019). Pollinator communities have been studied with time-lapse-photography and video monitoring as well (Biella et al., 2019; Sakata et al., 2014).

The need to answer these research questions related to climate change is undeniable but the required equipment can be costly, especially when deployed in large numbers, and still requires manual system checks (i.e. periodically checking if the system is operating, replacing batteries, downloading data, ...). The rise of microcontrollers (e.g. Arduino) and single-board computers (e.g. Raspberry Pi (Jolles, 2021)), now enables the development of highly affordable solutions (Dolgin, 2018), that can also reduce the need for system checks when connected to a central server. Microcontrollers and single-board computers are small computers manufactured to control the functioning of instruments, such as cameras or sensors. For pollinator studies for instance, microcontrollers could be used that combine time-lapse photography with motion detection to camera trap pollinators. These microcontrollers are rapidly evolving and are often surprisingly cheap and energy efficient (Pieters et al., 2021). Many Internet of Things (IoT) communication technologies already exist to communicate between devices and upload data to a server that can be accessed from a computer, allowing remote control and online data storage (Akpakwu et al., 2017). For instance, Low Power Wide Area technologies (LPWA), such as LoRa (Vangelista et al., 2015) or SigFox (https://www.sigfox.com), are ideal for remote IoT applications because LPWA technologies allow long-range communication among IoT devices at low power consumption. However, this communication protocol is optimized for transfer of small amounts of data (e.g. microclimate sensors) but is not appropriate to transfer a continuous stream of photos. Wireless transmission of larger data volumes, like photos, can already be achieved using Bluetooth or Wi-Fi technologies, but these have evident disadvantages, such as being limited to areas with Wi-Fi coverage, having very low power efficiency or a short data transfer range. In the future, however, the upcoming 5G technology will be the answer, promising the previously unattainable combination of low power consumption and high data transfer rates (Akpakwu et al., 2017). The adoption of these technologies will strongly reduce chances of data loss and the number of field visits (e.g. to download data or to replace batteries), which can be very time consuming for researchers, especially in remote locations where undisturbed ecosystems are often located. In this way, these innovations can also allow for set-ups on a larger scale and a stronger research power. As a result, the effect of temperature on phenology and possible feedbacks on the pollinator community could be identified from the researcher's desk, using the smart combination of phenocams, insect camera traps and microclimatic sensors in micro-controllers that are installed in forests with different microclimates. A similar approach in a marine ecology context, where underwater time-lapse images were combined with temperature and salinity sensors, illustrated the potential of this approach to relate phenological shifts to environmental conditions (Sbragaglia et al., 2019). The relationship between temperature, phenology and pollination can then be used to predict phenological mismatches due to climate change.

Public archives

Public archives of photographs can be invaluable sources of information and lead to the development of new techniques and methods for studying ecological change (e.g. Deus et al., 2016; Graham et al., 2010; reviewed by Nesse & Airt, 2018). Public archives comprise Google Street View images, television archives, footage from public cameras (e.g. traffic, CCTV and surveillance cameras), webcams from ski resorts or beaches, etc. Advantages of using public archives as data sources are that it appears to be more time- and cost effective and has a lower carbon footprint than collecting data in a traditional manner (Kotowska et al., 2021). These advantages are amplified for global-scale studies, where traditional field sampling is very laborious.

Public archives represent a huge amount of image data that can be used in many research areas, but probably the most obvious ecological application is in urban ecology since most public cameras operate in urban areas (e.g. CCTV cameras). Some recent studies assess the usefulness of Google Street View to study the invasion of alien plant species in road verges (Collette & Pither, 2015; Deus et al., 2016; Kotowska et al., 2021), to record the number of urban street trees and estimate their diameter (Berland et al., 2019), to evaluate urban green ecosystem services such as cooling, air purification and noise attenuation (Barbierato et al., 2020), and to inventory the potential habitat for native pollinators in residential front yards (Burr et al., 2018). Some public archives also document more rural landscapes. De Frenne et al. (2018), for example, compiled a time-series of trees and shrubs recorded in TV footage of a professional road cycling race (the Tour of Flanders) in spring, to study the timing of leaf-out and flowering over four decades (1980-2016). Such widespread data from Google Street View or broadcast archives could be augmented with those from internet-connected public or private cameras to monitor effects of global environmental change on vegetation on a cross-continental scale (Graham et al., 2010).

Compared to repeat photography and time-lapse photography, public archive images as a data source are currently less represented in ecological studies (Fig. 2). However, given the rapid accumulation of publicly available digital data, including images, we expect the relative contribution of public archives to increase. Recently, the term *iEcology* (i.e. internet ecology) was introduced and defined as an emerging research approach that allows the study of ecological patterns and processes using online data generated for other purposes and stored digitally (i.e. *passive crowdsourcing*) (Jarić, Correia, et al., 2020). Of the four main data sources in iEcology (being text, images, videos and online activity), images are the most represented, especially for studies on plants. The most common applications of iEcology have been to explore species occurrences and their spatiotemporal trends, but also trait dynamics and evolutionary trends can be explored (see Jarić, Correia, et al., 2020 for a review). For instance, ElQadi et al. (2017) mapped species distributions of bees and flowering plants in Australia, based on geo-tagged images from social media. In addition to mapping the distribution and occurrences of known species, images uploaded on social media have also been used to identify new species (e.g. Gonella et al., 2015).

*Case study: combining Google Street View with citizen science to study plant species distribution at a global scale*

A highly promising, yet rarely explored source of spatial and temporal information is the large-scale database of Google Street View (GSV), which was established in 2007 and provides vast amounts of panoramic images at a global scale. Not only dedicated to cities and urban areas, GSV documents rural areas and remote places as well (with road access). GSV often provides multiple images of the same place, taken at different moments, allowing the assessment of temporal changes. One promising avenue for ecological change research is using this vast amount of data to study distribution of plant species on a global scale, advancing roadside ecology in particular. For example, Kotowska et al. (2021) used GSV to visually track the spread of *Solidago canadensis* and *S. gigantea*, two invasive alien plants from North America along road networks in Poland. They visually inspected transects of GSV images for the presence/absence of the invasive species. Similarly, Pardo-Primoy & Fagúndez (2019) used GSV to assess the distribution and recent spread of an invasive grass species in industrial sites in Galicia (Spain). Dyrmann et al. (2021) also showed that mapping of invasive plants along roadsides is possible based on images taken from a driving vehicle, although they did not use GSV, but used their own equipment to obtain such images. An important limitation of the GSV system is that images are not always taken on the same date, or even the same season. This reduces the probability of plants being detected (e.g. for species that are less distinct when not flowering) and makes GSV less suitable for e.g. phenology studies (Dyrmann et al., 2021; Kotowska et al., 2021).

Although these example studies report that the use of GSV is much more time- and cost effective than collecting data through field sampling, the visual screening of GSV images for studies at large spatial scales remains time consuming. Here, citizen science platforms could be of aid for identifying target species on GSV images. While this has not yet been done in plant distribution studies, successful examples from other research fields have proven its potential. Leighton et al. (2016), for instance, developed an open source web application which facilitates data extraction from Google images through a customized survey, and applied it to several case studies, such as the geographical distribution of black bear colour morphs and barn owl melanin-based ornamentation. This software could easily be adapted to allow the use of citizen scientists that can fill in such surveys for a set of GSV images from target locations. In a study on restoration planning, citizen scientists were used to identify degraded areas through Google Earth, after a short training session (Rowe et al., 2021). Google Street View could be applied in similar ways, but with an even higher spatial resolution, e.g. by training citizen scientists to recognize particular landscape features or plant species. In 2013, an extensive Street View Imagery of the Galapagos Islands was launched, together with the citizen-science initiative 'Darwin for a day', where the public could help identify plants and animals observed when navigating through the imagery (McCarthy, 2015). With the arrival of *Street View Trekkers*, more and more off-road remote areas are now also represented in Google Street View. As the density of the GSV network will keep increasing, it is likely that the value and potential of the GSV system for ecological studies will also further increase (Rousselet et al., 2013).

Applying citizen science to process large amounts of images could thus enable us to study plant species distribution on a global scale for multiple conspicuous invasive species such as *Reynoutria japonica*, *Rhus typhina* and *Senecio inaequidens.* In addition, also the fast advances in automated image processing and identification tools (see **Box 2**) will allow global scale analyses of GSV images in the future. In a next step, the distribution of (invasive) plant species obtained from GSV images can be linked to change drivers or more specifically roadside vegetation management (e.g. Jakobsson et al., 2018). Apart from studying species distribution, other promising applications of GSV images are ground truthing of remote sensing imagery (e.g. Yan & Ryu, 2021) or detection of tree vitality (Kälin et al., 2019).

**Box 2: from images to knowledge**

Translating timeseries and/or pairs of photographs into ecological knowledge requires a series of image processing steps. These can be carried out manually, based on a human interpreter (e.g. De Frenne et al., 2018; Retka et al., 2019), but also automatically when a large number of photographs needs to be processed or when features are difficult to detect visually. Image processing generally includes (1) a preprocessing step, (2) an image processing step and (3) a data extraction step. The importance and necessity of each of these steps largely depends on the endpoint of the analysis and the types of photographs to be analysed (**Fig. 1 box 2**). These steps can be either performed on individual images taken at different points in time ( e.g. Correia et al., 2020) or on one composite image that integrates multiple recordings in time in one image (similar as done in remote sensing applications; see e.g. Coppin et al., 2004).

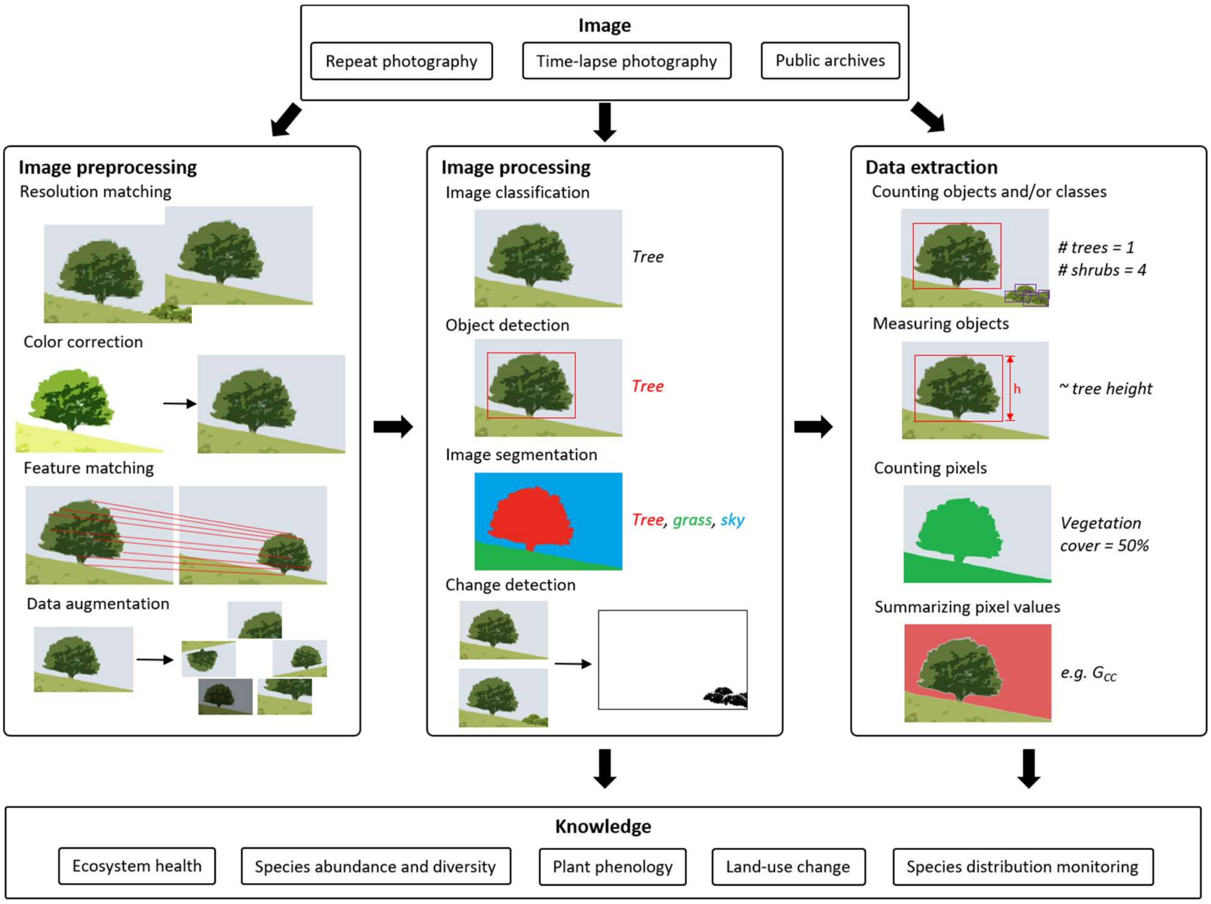


**Fig. 1 box 2. Schematic workflow to translate images into ecological knowledge**, through three steps: a preprocessing step, an image processing step and a data extraction step. Visual examples are given of what could be done in each of these steps. The black arrows indicate possible workflows, and show that not every step is always necessary (depending on the endpoint of the analysis and the types of photographs). $G_{CC}$ = Green Chromatic Coordinate.

**Image preprocessing** includes all steps that **enable a direct comparison of the ecological features of interest** in each photograph. If colours or vegetation indices need to be compared, colour correction might be needed (e.g. Gasparini & Schettini, 2003). For analyses of vegetation cover change, matching the spatial extent might be required as well (e.g. Michel et al., 2010). If an image overlay is needed for further analyses, both the extent and resolution need to be matched. These steps can be carried out manually (e.g. Michel et al., 2010) or automatically, via feature matching (e.g. Zhu et al., 2021) combined with down- or upsampling algorithms (e.g. Kälin et al., 2019; Monkman et al., 2019; Wang et al., 2020; Zhang et al., 2020). In general, time-lapse photography analyses require less preprocessing than repeated photography analyses as sensor type and viewpoint are generally kept constant. Finally, for some image processing steps, generating additional image data might help to boost the performance of an image classification tool (e.g. Correia et al., 2020; Kälin et al., 2019). In this so-called data augmentation step, new images are generated by mirroring, recolouring or cropping the original images.

**Image processing** includes all steps that **identify the ecological features of interest**. This identification can occur on an image basis (e.g. Price Tack et al., 2016), or on an object basis (e.g. Høye et al., 2021). Object identification algorithms either aim at drawing bounding boxes around a set of objects in a photograph (e.g. Marini et al., 2018; Monkman et al., 2019) or aim at ascribing each pixel to a specific object class, i.e. image segmentation (e.g. Bayr & Puschmann, 2019; Ott et al., 2020). Although human interpreters often outperform computer-assisted classification approaches, the latter are necessary when large amounts of photographs need to be analysed. Recent advances in machine learning, and more specifically, deep learning for image recognition have led to readily available neural networks that can be applied, amongst others, for image classification, object detection and image segmentation (e.g. Correia et al., 2020). Some of these existing models enable species-level identification of fauna and flora (e.g. Mesaglio & Callaghan, 2021), the identification of functional traits (e.g. Li et al., 2020), or the annotation of plant phenophases (Reeb et al., 2022). In contrast to these object-oriented processing techniques, ecological change can also be assessed using pixel-based change detection algorithms. These pixel-based approaches, based on image overlays, aim specifically at identifying changed pixels by e.g. subtracting two photographs, pixel by pixel (see Coppin et al., 2004, for an overview).

**Data extraction** translates the content generated during the image processing step **into data that can be used for the analyses of ecological change**. In analogy to the processing step, this data extraction step can also occur on a pixel basis or an object basis. This step generally involves basic mathematical operations such as counting pixels (e.g. estimating vegetation cover; e.g. Jean et al., 2015) or objects (e.g. counting the number of buds on a plant; e.g. Correia et al., 2020), estimating object dimensions (e.g. calculating the height of an object's bounding box; e.g. Barrett & Brown, 2012), or summarizing the pixel values of a certain object (e.g. the average greenness value of a vegetation patch; e.g. Filippa et al., 2016).

**Future perspectives**

Our review clearly illustrates that close-range imaging has a lot of potential for studying ecological change at various scales. Due to ongoing methodological, technological and analytical developments in image processing software and hardware, we expect that the range of possibilities associated with photographs in ecological research will extend significantly in the near future (Jarić, Roll, et al., 2020). Below, we will discuss some key developments and the associated possibilities they create for using photos in ecological change research.

First of all, we expect that baseline images will become more and more accessible, due to ongoing digitization efforts of herbaria and natural science collections (see, for example, Dornelas et al., 2018; Hedrick et al., 2020), and the development of crowdsourcing initiatives (see e.g. case study 1: invite people to upload old photos on web-based platforms). Second, contemporary image recording will likely increase due to the increasing availability of cheap microcontrollers and processors that enable the development of low-cost time-lapse or motion-triggered cameras (e.g. Steen, 2017) that can be deployed in large numbers to monitor along wide environmental gradients, potentially replacing labour-intensive monitoring programs. The upcoming 5G technology will facilitate such large scale studies by enabling remote image transfer (Akpakwu et al., 2017) (see case study on time-lapse photography). In addition, technological advances in other fields such as in self-driving vehicles may further accelerate the availability of recorded images in landscapes (Barbierato et al., 2020), including remote and scarcely populated areas (Warren-Rhodes et al., 2007).

This increase in availability of image data, however, will only be of interest for ecological research if image processing evolves towards automatic processing, using machine learning tools, with deep learning being the most promising. With the digitization of our society but also the development of faster computing infrastructure and the evolution of neural network algorithms, deep learning techniques are indeed increasingly being adopted for many different purposes. Although recent advances in this field predominantly focus on applications in agriculture (see, for example, Li et al., 2020), some of these advances can be applied to plant science in general, including automatic image segmentation and feature extraction (e.g. Ott et al., 2020), phenotyping (e.g. for the quantification of plant traits (Li et al., 2020) or tree dimensions (Barrett & Brown, 2012)) and automatic species identification (e.g. to study biodiversity or species ranges (Dutta et al., 2021)). Especially the concept of transfer learning, using models trained for a specific image processing task to perform a related task, potentially even in a different scientific field, is promising for the study of ecological change, where labelled image data for model training is currently still scarce (e.g. Heredia, 2017; Schindler & Steinhage, 2021; Younis et al., 2020). Using this concept, models trained on a collection of freely available labelled images from trivial subjects such as cats, cars or houses (e.g. ImageNet (Deng et al., 2009) or MS COCO (Lin et al., 2014)) can be used as a basis for training a model to identify plants, species or vegetation types. With pre-training, the neural network acquires information on the structure and nature of images in general, such as recognizing edges and objects, which allows for faster learning on the target images. As a result, transfer learning diminishes the necessary amount of study-specific labelled image data, and dramatically decreases the time needed for model training, a process that can take up to a few weeks and requires high computational power.

Although this technology will make photo-based phenotyping become common practice in many fields, it probably will be of limited use to study long-term changes in plant traits as photos need to fulfil several requirements depending on the trait being investigated (e.g. perpendicular to leaf surface for leaf area measurements and with a known scale to translate photo-based dimensions to real-life dimensions for measuring plant organ surfaces or lengths). There are, however, some exceptions. Phenological traits, such as leaf-out or flowering dates, can often be easily measured provided that the exact date of the photo is known. Also, the quantification of trait variability within one image should be a possibility, both for old and new images. Finally, also studying long-term changes in count-based traits such as number of leaves or flowers should be possible based on photographs.

Another important aspect that can potentially boost the future use of images in ecological research is the rising popularity of citizen-science projects. This is a form of *active crowdsourcing*, involving active contributions from citizens typically motivated by the desire to aid a worthy cause (See et al., 2016). Since cameras are omnipresent in our society, predominantly those of smartphones, citizens can easily gather image data with a minimum of guidance (e.g. Hampton et al., 2013; Marcenò et al., 2021). With the development of smartphone apps for ecology (Rudic et al., 2020), citizen-science projects that combine this technology with expert knowledge are now characterizing as many species possible during one or multiple day "Bioblitzes" (Nicolai et al., 2020). In a recent study, Gordoa et al. (2018) used images from free-diving underwater fish photography contests as a complementary tool for assessing littoral fish communities. The development of online tools to enable citizens to share their (preferably annotated) images in a structured way (e.g. Boho et al., 2020), will be important to increase the availability of such images for scientists. The increasing popularity of citizen-science platforms to share nature observations, such as iNaturalist (https://www.inaturalist.org/; Mesaglio & Callaghan, 2021), highlights their potential to collect large quantities of data at little cost. As such data will often be noisy, due to differences in light conditions, sensor quality, background characteristics, etc., the use of deep learning tools for automatic image segmentation and feature extraction will be key to make sense of such data in the future (Singh et al., 2018).

Furthermore, ecologists should continue to investigate the possibilities of social media as an emerging source of data, and photos in particular. This is a form of *passive crowdsourcing*, based on online data that were generated for other purposes (Jarić, Correia, et al., 2020). Social media data are generally referred to as 'big data' (Crampton et al., 2013; Kitchin, 2014), and the volume of user-generated data worldwide is overwhelming (Toivonen et al., 2019). Social media data have a high potential for providing novel insights on human-nature interactions for conservation, e.g. through analyzing species' popularity and associated sentiment, monitoring wildlife trade online, or assessing nature-based recreational preferences (Correia et al., 2021). Online hunting photos from social media were, for instance, used to assess the factors that drive satisfaction from trophy hunting (Child & Darimont, 2015). Retka et al. (2019) used photographs from the social media platform Flickr to map cultural ecosystem hotspots in a marine protected area. Recently, Fox et al. (2020) developed a tool to harvest large datasets from Flickr in a reproducible way. In addition to identifying new research avenues for applying social media data in ecology, the establishment of new mechanisms to enable social media users to actively "donate" their data for research purposes via platforms, should be explored. When interpreting results based on social media data, researchers must carefully consider ethical issues (Zook et al., 2017). Privacy and data anonymization should be considered even if using publicly shared content (Toivonen et al., 2019).

To take advantage of the true potential of the discussed methods for enhanced data acquisition and processing, it is important to take into account their concomitant requirements. This involves the widespread adoption of data standards by the ecological science community and making sure that data and developed models are findable, accessible, interoperable and reusable (c.f. principles of 'FAIR data'; Wilkinson et al., 2016). Most importantly, for these novel techniques to be applied in ecological research, it is imperative for ecologists to follow specialized training on artificial intelligence algorithms and/or increase collaborations between the fields of ecology and computer science.

**Conclusions**

In a rapidly changing world, ecologists need to exploit all possible data sources to increase their understanding of ecosystem responses. Photography can fundamentally contribute to this understanding, but is currently outside the toolkit of most ecologists. Different methods of photography have their own strengths and opportunities, and may provide us with insights that are difficult, or even impossible, to generate in any other way. Historical photographs are often the only data source to characterize vegetation of the past, and hence an essential tool to quantify long-term vegetation changes. The use of time-lapse cameras may provide an alternative for time consuming observational field studies, in particular when it can be combined with real-time data-upload online and automated image processing. The possibility to install global networks of these cameras, can help to reveal global trends in vegetation ecology. Public archives, such as Google Street View or traffic and surveillance cameras, contain an unprecedented amount of information at a local scale, and allow to study a variety of ecological processes, across large spatial and temporal scales, without even leaving the office.

To exploit the full potential of photos for ecological change research, we need to invest not only in technological advances to process and collect images but also in proper data management. Ecologists need to treat their photos (and their data in general) as an enduring product of research, and therefore must (i) organize, document and preserve them for posterity, (ii) share them (e.g. through university libraries, professional journals, or data federations such as DataONE), and (iii) collaborate with networks of colleagues to bring together photographic data (Hampton et al., 2013).

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