IBIS
international journal of avian science
Ibis (2024) doi: 10.1111/ibi.13317

Using citizen science image analysis to measure seabird phenology

ALICE J. EDNEY,*[1] JÓHANNIS DANIELSEN,[2] SÉBASTIEN DESCAMPS,[3] JÓN EINAR JÓNSSON,[4] ELLIE OWEN,[5] FLEMMING MERKEL,[6,7] RÓBERT A. STEFÁNSSON,[8] MATT J. WOOD,[9] MARK J. JESSOPP[10,11] & TOM HART[12]

[1]*Department of Biology, University of Oxford, 11a Mansfield Road, Oxford, OX1 3SZ, UK*
[2]*Faroe Marine Research Institute, Havstovan, Nóatún 1, FO-100 Tórshavn, Faroe Islands*
[3]*Norwegian Polar Institute, Framsenteret, 9296, Tromsø, Norway*
[4]*Research Centre at Snæfellsnes, University of Iceland, Hafnargötu 3, 340, Stykkishólmur, Iceland*
[5]*National Trust for Scotland, Balnain House, 40 Huntly Street, Inverness, IV3 5HR, UK*
[6]*Department of Ecoscience – Arctic Ecosystem Ecology, Frederiksborgvej 399, Roskilde, 4000, Denmark*
[7]*Greenland Institute of Natural Resources, Kivioq 2, PO Box 570, 3900, Nuuk, Greenland*
[8]*Iceland Nature Research Centre (Náttúrustofa Vesturlands), Hafnargötu 3, 340, Stykkishólmur, Iceland*
[9]*School of Natural & Social Sciences, University of Gloucestershire, Francis Close Hall, Cheltenham, GL50 4AZ, UK*
[10]*School of Biological, Earth & Environmental Sciences, University College Cork, Distillery Field, North Mall, Cork, T23 N73K, Ireland*
[11]*MaREI Centre, Environmental Research Institute, University College Cork, Beaufort Building, Ringaskiddy, P43 C573, Ireland*
[12]*Oxford Brookes University, Gypsy Lane, Headington, Oxford, OX3 0BP, UK*

Developing standardized methodology to allow efficient and cost-effective ecological data collection, particularly at scale, is of critical importance for understanding species' declines. Remote camera networks can enable monitoring across large spatiotemporal scales and at relatively low researcher cost, but manually analysing images and extracting biologically meaningful data is time-consuming. Citizen science image analysis could reduce researcher workload and increase output from large datasets, while actively raising awareness of ecological and conservation issues. Nevertheless, testing the validity of citizen science data collection and the retention of volunteers is essential before integrating these approaches into long-term monitoring programmes. In this study, we used data from a *Zooniverse* citizen science project, *Seabird Watch*, to investigate changes in breeding timing of a globally declining seabird species, the Black-legged Kittiwake *Rissa tridactyla*. Time-lapse cameras collected >200 000 images between 2014 and 2023 across 11 locations covering the species' North Atlantic range (51.7°N–78.9°N), with over 35 000 citizen science volunteers 'tagging' adult and juvenile Kittiwakes in images. Most volunteers (81%) classified images for only a single day, and each volunteer classified a median of five images, suggesting that high volunteer recruitment rates are important for the project's continued success. We developed a standardized method to extract colony arrival and departure dates from citizen science annotations, which did not significantly differ from manual analysis by a researcher. We found that Kittiwake colony arrival was 2.6 days later and departure was 1.2 days later per 1° increase in latitude, which was consistent with expectations. Year-round monitoring also showed that Kittiwakes visited one of the lowest latitude colonies, Skellig Michael (51.8°N), during winter, whereas birds from a colony at similar latitude, Skomer Island (51.7°N), did not. Our integrated

*Corresponding author.
Email: alice.edney@biology.ox.ac.uk
Twitter ID: animal__alice

time-lapse camera and citizen science system offers a cost-effective means of measuring changes in colony attendance and subsequent breeding timing in response to environmental change in cliff-nesting seabirds. This study is of wide relevance to a broad range of species that could be monitored using time-lapse photography, increasing the geographical reach and international scope of ecological monitoring against a background of rapidly changing ecosystems and challenging funding landscapes.

Keywords: Cameras, citizen science, phenology, seabirds.

Biodiversity loss is threatening ecosystems, but there is increasingly limited time and funding for conservation (Waldron *et al.* 2013). Developing methods for cheaper, safer and more efficient ecological data collection is therefore of increasing importance to understand how and why species are declining, and to implement effective ecosystem management.

Seabirds are among the most threatened groups of vertebrates, with almost half of species globally threatened or near threatened with extinction (Croxall *et al.* 2012, Phillips *et al.* 2023). Although seabirds are a well-studied faunal group (Richards *et al.* 2021), monitoring seabirds on land during the breeding season and at sea is often challenging (Edney & Wood 2021). Difficulties accessing, viewing and disturbing breeding seabirds, as well as the time and money required to collect detailed life-history data (e.g. on phenology, breeding success, survival and diet) have often limited the scale of monitoring and precluded a globally standardized methodology (Mitchell & Parsons 2007, Paleczny *et al.* 2015, Merkel *et al.* 2016, Edney *et al.* 2023).

Remote photography has a long history in seabird monitoring but has typically been limited to studies at a single site or conducted over a short time-period, often observing animals opportunistically, using handheld or animal-triggered cameras (Black *et al.* 2018a, De Pascalis *et al.* 2018, Johnston *et al.* 2019). However, increased affordability, and continued improvements in power and data storage solutions, mean that large volumes of digital imagery can now be collected and stored with comparative ease (Bolton *et al.* 2007). This has seen the field of time-lapse photography (which records images at predetermined time intervals regardless of subject presence) rapidly expand in recent years (Edney & Wood 2021). Remotely operated camera networks can enable monitoring across species' ranges, in remote locations and harsh conditions, at relatively low researcher cost and effort, as cameras need generally only be attended once per year (Southwell & Emmerson 2015, Black 2018, Edney & Wood 2021). Collecting data year-round allows measurements of key breeding parameters, as well as additional variables such as colony arrival, colony departure and winter colony attendance, which are not captured by 'standard' fieldwork, which typically focuses on determining breeding population counts and breeding success (Walsh *et al.* 1995, Black *et al.* 2017, 2018a). Higher frequency of observations than traditional fieldwork, which is often limited to a few repeat visits per season, can also provide finer temporal resolution data, potentially allowing dates of phenological events (e.g. chick hatch, fledge or failure) to be measured more precisely (Walsh *et al.* 1995, Black *et al.* 2018b). This can improve understanding of factors affecting chick survival or changes in fledging duration, for example (Knudson *et al.* 2020). Nonetheless, analysing images and extracting biologically meaningful data takes time, resulting in researcher workload being moved from the field to the desk (Merkel *et al.* 2016, Pascalis *et al.* 2018). One potential solution to prevent image collection exceeding researchers' processing capabilities is crowd-sourcing.

Citizen science engages non-professionals in scientific research (Dickinson *et al.* 2012) and has a long-standing history in ecology and conservation (Kobori *et al.* 2016, Swanson *et al.* 2016). Volunteers are primarily motivated to contribute to science, and citizen science projects can be effective in raising public awareness of ecological issues and increasing environmental stewardship (Raddick *et al.* 2010, Swanson *et al.* 2016, Viola *et al.* 2022). Despite this, citizen science projects often suffer criticism from professional researchers about the validity of data derived from non-experts, which can lower publication rates and grant funding (Foster-Smith & Evans 2003, Dickinson *et al.* 2010, Bonter & Cooper 2012, Swanson *et al.* 2016). It is therefore important that studies using citizen science data test that data's robustness before use (Hertzog *et al.* 2021, Gorleri *et al.* 2022, Jäckel *et al.* 2023). Citizen science projects have used a range of methods to improve the quality of volunteer data, including training volunteers before participation, requiring volunteers to pass a competency test, or aggregating the results of multiple users to form a consensus (Dickinson *et al.* 2010, Swanson *et al.* 2016). Recruiting enough volunteers to meet project workload is a further consideration for citizen science projects, and retaining volunteers can help to ensure project longevity, as well as minimizing the need for frequent training and/or testing of new participants.

When testing any new methodology, it is essential that it is ground-truthed against a well-understood phenomenon, but one which is of fundamental importance. Changes in the timing of key life cycle events (phenology) are one of the best-documented responses to rising global temperatures (Møller *et al.* 2008). Phenology of species occupying higher trophic levels, such as seabirds, may be less responsive to temperature-driven environmental change than those occupying lower trophic levels (Thackeray *et al.* 2010, 2016, Burthe *et al.* 2012, Keogan *et al.* 2018), making seabirds particularly sensitive to trophic mismatch (Hipfner 2008, Shultz *et al.* 2009, Regular *et al.* 2014). This effect may be greater at higher latitudes, where Arctic amplification means Arctic ecosystems are being disproportionately affected by warming; yet, harsh abiotic conditions severely limit the time window that is favourable for seabird breeding and migration (Descamps *et al.* 2019, Sauve *et al.* 2019, Whelan *et al.* 2022). The timing of breeding is expected to be later at higher latitudes, driven by physical conditions (such as snow/ice cover on nest-sites) delaying the onset of breeding and/or by the timing of food availability near the colony (Moe *et al.* 2009, Burr *et al.* 2016). Investigating phenological changes across species' latitudinal breeding range is therefore important to assess which populations may be most at risk from trophic mismatch in a changing climate.

In this study, we investigated the potential for citizen science analysis of images collected from a time-lapse camera network, to measure breeding phenology of a globally declining seabird species (BirdLife International 2023), the Black-legged Kittiwake *Rissa tridactyla* (hereafter Kittiwake). Many bird phenology studies focus on a single species and site, while those spanning large spatial and temporal scales often rely on varying methods within the same study (Frederiksen *et al.* 2004, Moe *et al.* 2009, Wanless *et al.* 2009, Keogan *et al.* 2022) to obtain measures of breeding phenology across different sites and years (e.g. using both observed and estimated dates; using a combination of first, mean or median dates; changes in frequency and/or intensity of nest checks over time) meaning results are not always directly comparable and there is a clear need for standardization. We collected images at 11 colonies spanning an extensive latitudinal gradient (51.7°N–78.9°N), providing a non-invasive, standardized technique for collecting data in remote locations that are visited infrequently by humans and often previously unmonitored (Edney & Wood 2021). To process the large volume of imagery collected, we asked volunteers from the *Zooniverse* citizen science project, *Seabird Watch*, to classify adult and chick Kittiwakes in these images (www.seabirdwatch.org). We tested the validity of citizen science data when images were classified by multiple volunteers and a consensus value was used, and predicted that such techniques would yield similar results to 'expert' image annotation by a researcher. Using this standardized method would then enable assessment of spatiotemporal patterns of colony attendance, and we predicted that Kittiwake arrival and departure would be delayed per degree increase in latitude, corresponding to the delayed egg-laying and hatching observed in previous studies (Burr *et al.* 2016, Keogan *et al.* 2022). We further considered the overall cost-effectiveness (both time and money) of the citizen science camera network. We predicted a monotonic relationship between the length of time volunteers participated in the project and the number of images they classified, in support of the idea that volunteer retainment is key to the system's long-term capacity to answer advanced ecological questions pertaining to seabird ecology and demography, in a standardized way.

METHODS

Study sites and camera set-up

We used a network of 11 time-lapse cameras across eight countries that span the latitudinal breeding range of the Black-legged Kittiwake

(Fig. 1). The time-lapse cameras were most often commercially available Reconyx Hyperfire or Reconyx Ultrafire (Reconyx Inc., Holmen, WI, USA) mounted on either a pre-made camera tripod or a custom-built tripod (e.g. with scaffold poles), although some sites had specialist, custom-built cameras (Table 1, Fig. 2). Tripods were weighed down with ballast stones or attached to the ground/nearby rock to prevent movement. Each Reconyx camera contained a 16–64 GB SD card and 12 Ultimate Lithium batteries, or at UK sites, 12 rechargeable Eneloop batteries. Most cameras captured between 30 and 130 nests and were programmed to take one image per hour year-round, although at high latitudes this was sometimes reduced to four photos per day to maximize battery lifespan at sites that were infrequently visited (e.g. in Alkefjellet, Svalbard, a Reconyx Ultrafire captured four images per day from 2018 to 2022, before its retrieval in 2022). Typically, batteries and SD cards only need to be changed once every 1–2 years for Reconyx cameras taking hourly images. The total cost of setting up one Reconyx camera is in the region of £800 (excluding travel expenses), depending on the camera model and mount used, and quantities ordered (e.g. c.£500–£600 per Reconyx camera; c.£200 per tripod; c.£20–£30 for batteries and SD cards). Cameras were visited once every 1–4 years depending on access and logistical constraints, to replace SD cards and batteries.

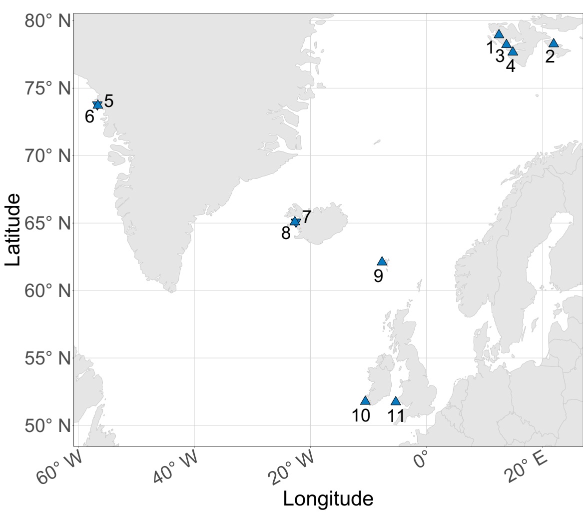

Figure 1. Locations of cameras included in this study. Key: 1 = Ossian Sarsfjellet, 2 = Kapp Waldberg, 3 = Alkhornet, 4 = Midterhukfjellet, 5 = Apparsuit, 6 = Kippaku, 7 = Elliðaey, 8 = Hvítabjarnarey, 9 = Mykines, 10 = Skellig Michael, 11 = Skomer. Closely spaced colonies are illustrated using upward and downward triangles to avoid complete overlap.

Camera data extraction

Image annotation and processing

Images were annotated by volunteers on the *Seabird Watch* citizen science project (www.seabirdwatch.org), hosted on the *Zooniverse* platform (www.zooniverse.org). The *Seabird Watch* project contains multiple 'workflows' (sequences of tasks, which volunteers are asked to complete) for analysing different image sets. Each workflow shows users a tutorial before being given their first image, which explains how to complete each task and provides examples of how birds appear in images. There is also a field guide of animals likely to be seen, a Frequently Asked Questions page and a discussion forum moderated by scientists, to answer volunteer questions and help ensure they understand the tasks to complete. For this analysis, the 'Timelapse' workflow (launched on 19 October 2017) was used to click on birds and classify them as either adult or chick Kittiwakes. Each image was viewed by multiple volunteers to increase data reliability. Specifically, four people were initially shown each image, and if any of them classified a bird, then the image was shown to 10 people in total. If the first four volunteers classified zero birds, the 'blank' image was retired, meaning it was removed from the active dataset and not seen by further volunteers. As the presence of birds was easy to detect, recording four negatives was sufficient to be confident no birds were present and retire an image. Participants did not have to classify every bird in images, to help prevent loss of interest when photographs contained a large number of individuals, but at the end of each image, they were asked to select 'Yes' or 'No' for whether they had marked every bird (Jones *et al.* 2018). Previous research showed that for five colonies sampled, > 99% of images were classified by four or more volunteers who marked all birds, and > 47% were classified by seven or more volunteers who marked all birds (Edney 2020). This suggests that across at least 10 independent viewers almost every bird should be classified.

As each image was classified by multiple volunteers, a clustering algorithm was used to aggregate raw classifications to generate one 'consensus

Table 1. Type of camera installed at each location used in this study.

Site (colony code)	Latitude, longitude	Year	Camera type
Skomer Island, Wales (SKOM)	51.74, −5.30	2017	Reconyx UltraFire
		2018, 2019, 2020	Reconyx HC500 Hyperfire
Skellig Michael, Ireland (SKEL)	51.77, −10.54	2014, 2015, 2016	Reconyx HC500 Hyperfire
		2018, 2019, 2020, 2021	Reconyx Ultrafire
Mykines, Faroes (MYBR)	62.1, −7.66	2014, 2015	Reconyx HC500 Hyperfire
		2018	Reconyx Hyperfire 2 Covert
		2019, 2020	Reconyx HF2 Pro Convert
		2021	Reconyx Ultrafire
Elliðaey Island, Iceland (ELLI)	65.09, −22.49	2015, 2016, 2017	Reconyx HC500 Hyperfire
Hvítabjarnarey Island, Iceland (HVIT)	65.08, −22.68	2016, 2017	Reconyx HC500 Hyperfire
		2018, 2019, 2020, 2021	Bushnell
Kippaku Island, Greenland (KIPP)	73.72, −56.63	2016, 2017, 2018, 2019	Canon EOS 60D mounted in weatherproof box (see Merkel *et al.* 2016)
Apparsuit Island, Greenland (APPA)	73.79, −56.72	2017, 2018, 2019	Canon EOS 70D mounted in weatherproof box (see Merkel *et al.* 2016)
		2020	Canon EOS 80D mounted in weatherproof box (see Merkel *et al.* 2016)
Midterhukfjellet, Svalbard (MITT)	77.66, 14.88	2014, 2015	Reconyx HC500 Hyperfire
		2016, 2017	Reconyx SC950 Security
		2019, 2020, 2021	Reconyx UltraFire
Alkhornet, Svalbard (ALKE)	78.21, 13.78	2015, 2016	Reconyx HC500 Hyperfire
Kapp Waldberg, Svalbard (KAPW)	78.27, 21.92	2017, 2018, 2019, 2020, 2021, 2022	Reconyx Ultrafire
Ossian Sarsfjellet, Svalbard (OSSI)	78.94, 12.49	2015, 2016, 2017, 2018, 2019, 2020, 2021	Reconyx HC500 Hyperfire

classification' for each object (i.e. bird) using Caesar software (Jones *et al.* 2018, Krawczyk *et al.* 2022). Classifications made by the same user in a single image (i.e. because they classified more than one bird) were placed in separate clusters, and consensus classifications had to be formed from at least three raw classifications to limit erroneous clicks (Jones *et al.* 2018, Krawczyk *et al.* 2022). The number of consensus classifications per image for each category (adult Kittiwake, chick Kittiwake) was summed to give an image count.

Images taken at 'night' were removed from the dataset post-clustering, using the 'suncalc' package in R to either identify images taken after sunset but before sunrise, or at high latitude, to identify images without sunrise or sunset between October and February. This was important because the cameras do not have night vision, and so a count of zero birds in completely dark images is not necessarily a true zero (i.e. there might have been birds present, but they could not be observed); this is particularly relevant at high latitudes in winter when the sun does not rise.

For this analysis, we used counts from the 1:00 PM image, or the time closest to 1:00 PM, for each day. This was because different camera set-ups and image times processed in *Seabird Watch* across sites and years meant not all hours were available for every camera.

Changes in arrival and departure with latitude

Count data for adult Kittiwakes were smoothed using a 3-, 5- and 7-day moving average to remove noise in the data. Smoothing was necessary because counts may be lower than expected (sometimes zero) as a result of the camera view being obscured, such as by snow, or a bird in the foreground partially obscuring the nests behind. The moving average chosen (i.e. 3, 5 or 7 days) was determined by comparison with researcher dates (see Citizen science data validation).

Figure 2. (a) Example time-lapse camera set-up on Skomer Island, Wales. This camera is mounted on a pre-made tripod typically used for spotting scopes, whereas other cameras are mounted on custom-built tripods made from scaffolding poles. Tripods are attached to the ground/nearby rock or weighed down with ballast. (b) Image taken at Skellig Michael, Ireland, in winter (12 November 2016), with Kittiwakes present on the cliffs.

We defined an observation period as starting on 1 January and ending on 31 December with arrival occurring between January and May and departure between July and December. Using these criteria, the available dataset for measuring colony arrival and departure was identified by removing years where the first image in the dataset was taken after May and where the last image in the dataset occurred before July (Table S1). Although we expected that Kittiwakes would not depart until August, we included July in the departure dataset to potentially identify colonies where all breeding attempts failed and Kittiwakes might leave early (Coulson 2011). This could facilitate further investigation on the effect of extreme events (e.g. severe predation, food shortage, bad weather) on Kittiwake breeding. Additional years were also removed where breaks in image capture (e.g. due to camera failure) meant arrival and/or departure were missed. Overall, 64% of possible arrival and departure dates were able to be used for analysis (Table S1).

Colony arrival was measured as the first day of X consecutive days of increase in the number of adult Kittiwakes, and colony departure was measured as the last day of X consecutive days of decrease in the number of adult Kittiwakes, where X took values from 2 to 7 days. The value of X used for analysis was chosen by comparison with researcher dates (see Citizen science data validation) and thus provides a standardized method to measure arrival and departure, as the same value of X could be used if the method were applied again in other studies. We used a consecutive days approach, rather than the first and last day an adult Kittiwake was recorded, to capture the gradual increase/decrease in colony abundance and reduce the likelihood of citizen science misclassifications recording too-early/too-late arrival/departure dates. For example, incorrectly classifying another bird species (such as a Herring Gull *Larus argentatus*, which may be present year-round in UK images) as a 'kittiwake' on 2 February, would give arrival as 2 February if this was the first day of the year a 'kittiwake' was seen. In comparison, the misclassified Herring Gull would be ignored using the consecutive days method, as it is unlikely that Herring Gull numbers would increase for multiple days in February.

We tested the relationship between latitude and arrival and departure dates using linear mixed-effects models, with either arrival or departure date as the response variable, latitude as a fixed effect and colony as a random effect, and computed P values using a Wald t-distribution approximation (Bates *et al.* 2015).

Citizen science data validation

We compared arrival and departure dates calculated from 2 to 7 days of consecutive increase/decrease using 3-, 5- and 7-day moving averages of *Seabird Watch* consensus classifications, with arrival and departure dates from manual researcher analysis. The researcher looked at the 1:00 PM images to identify the first time an adult Kittiwake was seen in an image (arrival) and the last time an adult Kittiwake was seen in an image (departure) for the season. Wilcoxon signed-rank tests tested for significant differences in *Seabird Watch* and researcher arrival and departure dates, for each combination of moving averages and consecutive days increase/decrease.

Citizen scientist participation and retention

To determine the long-term capacity of the camera–citizen science system to measure seabird

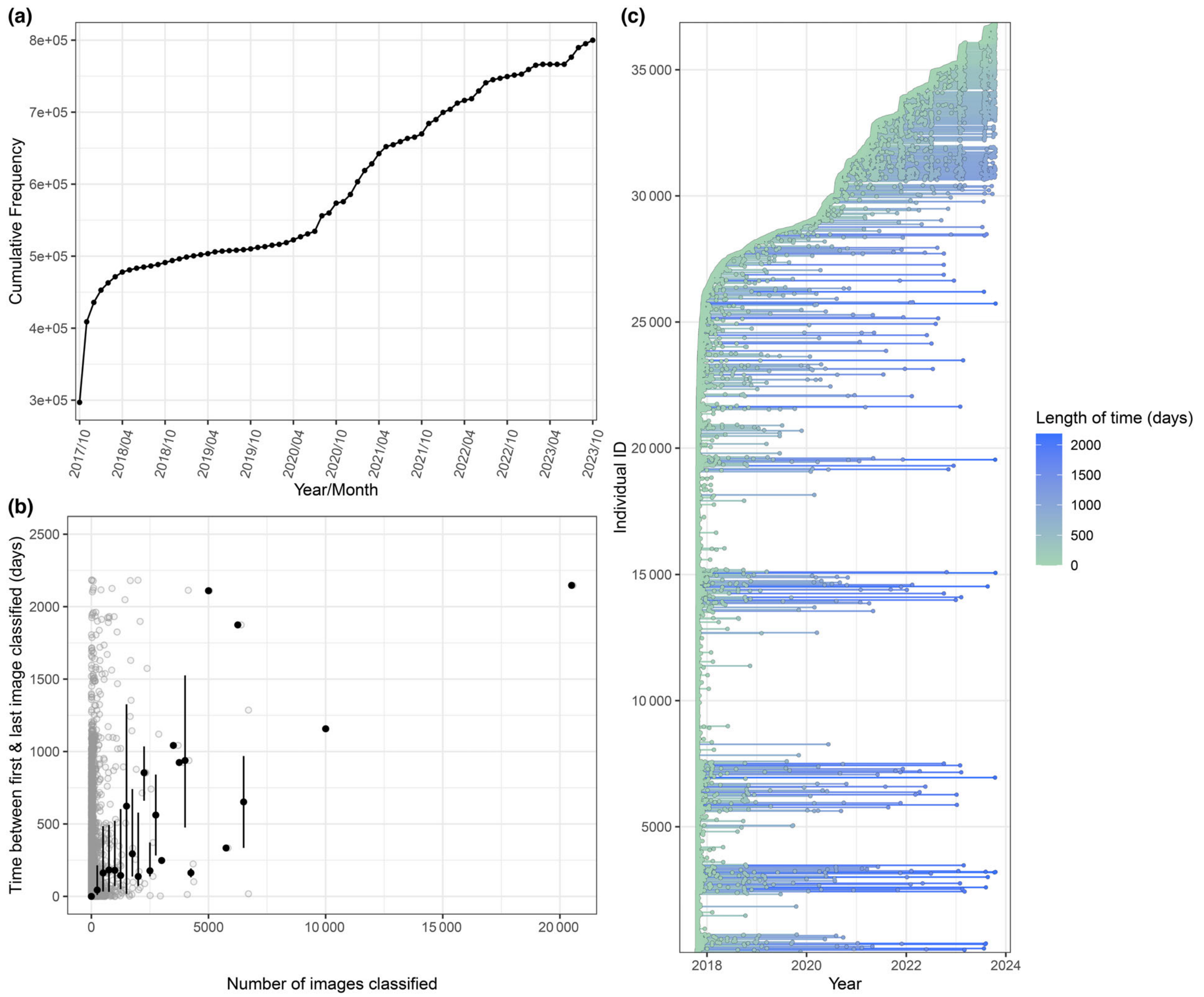

Figure 3. (a) The number of images classified using the *Seabird Watch* 'Timelapse' workflow (19 October 2017 to 2023) has steadily accumulated across time, with high initial uptake when the project launched, and another notable increase during the COVID-19 pandemic in 2020. (b) There is a positive correlation (r = 0.26, P < 0.001) between the number of images classified by each volunteer and the length of time between the first and last image they classified (n = 36 889). Points show raw data and transparency has been used to show density in areas of overlap. Black dots represent the median number of images classified, when binned into sets of 250, with whiskers showing the interquartile range. (c) Volunteer contribution pattern, showing the length of time (in days) between the first and last image each volunteer (individual ID) classified (n = 36 889).

demographic parameters, we extracted information on the number of images classified and volunteer contribution, for the 'Timelapse' workflow, from 19 October 2017 to 19 October 2023 (excluding April to June 2023 when the workflow was inactive). Specifically, we measured the median number of images classified per month, the median number of volunteers who classified at least one image per month, the number of images each volunteer classified in total and the time period over which these images were classified. A Spearman's rank correlation test tested for a correlation between the number of images each volunteer classified and the time period over which they classified these images. All analyses were conducted in R, version 4.2.2 (R Core Team 2022).

RESULTS

Citizen scientist participation and retention

From 19 October 2017 to 19 October 2023, 799 917 images were classified using the *Seabird Watch* 'Timelapse' workflow, which equates to

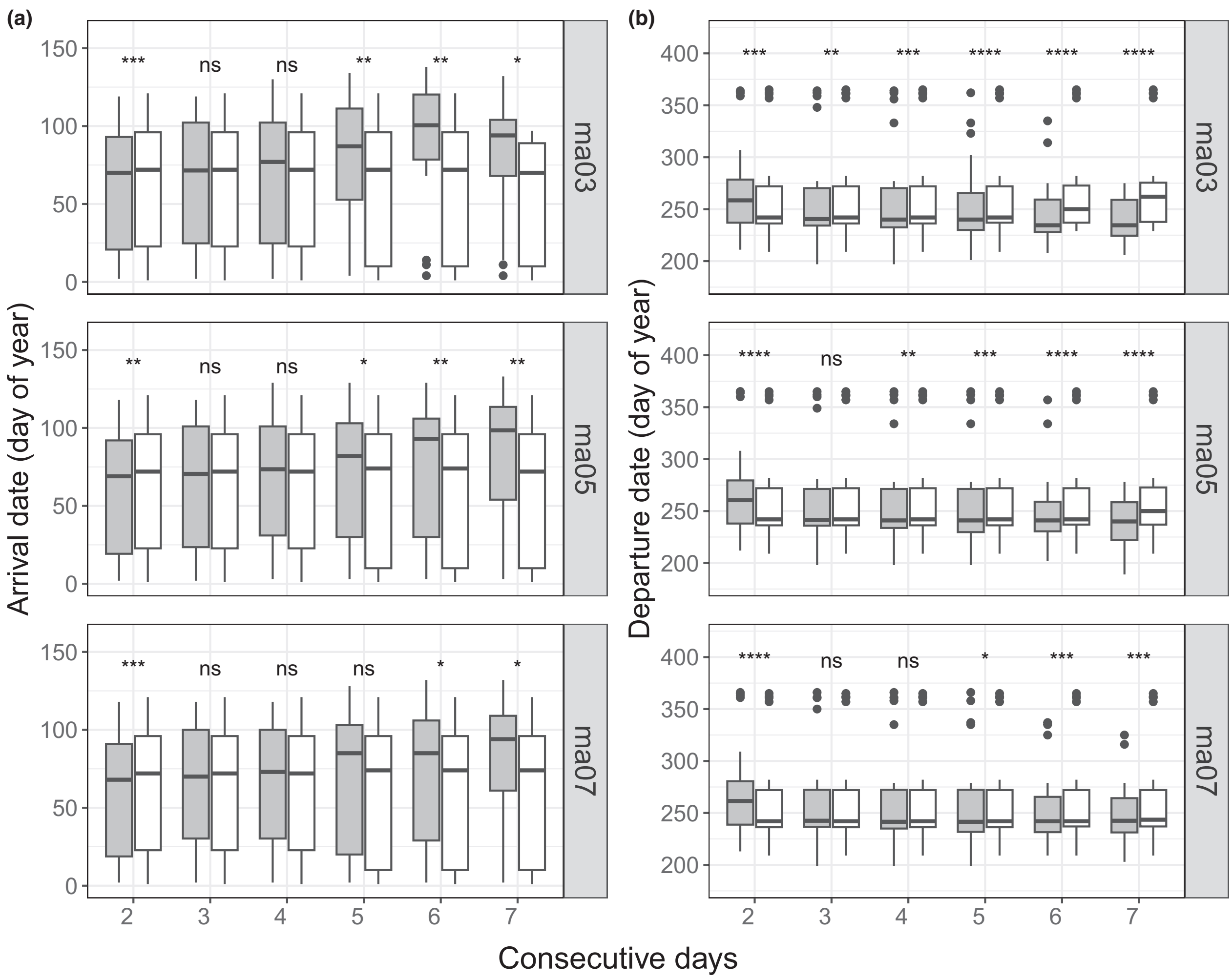

Figure 4. Boxplots comparing the median (a) arrival and (b) departure dates derived from citizen science consensus classifications (grey) and researcher analysis (white), when citizen science data were smoothed using 3-day (ma03), 5-day (ma05) and 7-day (ma07) moving averages, and arrival/departure was measured as the first 2, 3, 4, 5, 6 or 7 days of consecutive increase/decrease in the number of adult Kittiwakes, respectively. Researcher dates were obtained by manually looking at the images and recording the first (arrival) and last (departure) date an adult Kittiwake was seen at the colony each year. Outliers in (b) are departure dates from Skellig Michael, Ireland, where birds attended the colony over winter. Wilcoxon signed-rank tests tested for significant differences in citizen science and researcher arrival and departure dates, for each combination of moving averages and consecutive days increase/decrease.

87 046 unique camera images (because each unique image was classified four to ten times by different volunteers). The median number of images classified per month was 3846 (interquartile range (IQR) 2003–9576) and the maximum number of images was 296 921, in October 2017 (Fig. 3a). The total number of unique volunteers who classified an image was 36 889 (identified by their IP address or account login), of which 14 077 were logged into a registered account on the *Zooniverse* platform. The median number of unique volunteers participating per month was 193 (IQR 123–431), although the maximum was far higher (22 694 in October 2017). We found a positive correlation between the number of images classified by each volunteer and the length of time between the first and last image they classified ($r = 0.26$, $P < 0.001$; Fig. 3b), despite 81% of volunteers classifying images for only a single day (Fig. 3b,c). The median number of days between a volunteer's first and last classification was 0 (IQR 0–0) and the median number of images each volunteer classified during this time was 5 (IQR 2–12).

Citizen science data validation

Comparing arrival and departure dates derived from citizen science and researcher analysis, we found that the 5-day moving average was the smallest moving average that gave similar estimates for both arrival and departure, for at least one value of consecutive days increase/decrease (Fig. 4; Table S2, Fig. S1). The 5-day moving average was chosen to smooth the citizen science data going forward, as stronger smoothing using larger moving averages (e.g. 7 days) might reduce the ability to detect the timing of key breeding season events more precisely (e.g. the Kittiwake incubation period is typically 25–29 days; Coulson 2011). Using this 5-day moving average, arrival and departure dates were both similar when 3 days of consecutive increase/decrease were used to identify arrival/departure respectively (Fig. 4, Table S2, Fig. S1), and so arrival was measured as the first day of three consecutive days of increase, and departure as the last day of three consecutive days of decrease. For all combinations of moving averages and consecutive days, the departure dates for one colony, Skellig Michael, were outliers (departure date > q0.75 + 1.5*IQR; where q0.75 is the third quartile) (Fig. 4).

Changes in arrival and departure with latitude

Colony arrival and departure dates were determined by smoothing *Seabird Watch* consensus classification data using a 5-day moving average, and then determining the first day of 3 days of consecutive increase in number of adult Kittiwakes (arrival) and the last day of 3 days of consecutive decrease in the number of adult Kittiwakes (departure) (Fig. 5). Plotting the number of adult Kittiwakes (smoothed using a 5-day moving average) counted from consensus classification data showed that birds visited the Skellig Michael colony during winter, resulting in skewed 'departure' dates in December that did not reflect colony departure post-breeding (Fig. 5). Most Kittiwakes left the colony by mid-September and then returned in January before the start of the next breeding season, with small numbers of Kittiwakes present in between. Consequently, we excluded winter attendance and re-defined departure as occurring from July to 15 September for Skellig Michael (compared with July to December for all other colonies), and measured departure as the last day of three consecutive days of decrease within this time period. When all available *Seabird Watch* data were used, arrival was 2.6 (standard error (se) = ±0.71) days later per 1° increase in latitude ($t(18) = 3.66$, $P < 0.01$), and departure was 1.2 (se = ±0.49) days later per 1° increase in latitude ($t(36) = 2.42$, $P < 0.05$) (Fig. 6; arrival and departure data are provided in Tables S3 and S4).

DISCUSSION

Using images from the *Seabird Watch* time-lapse camera network, we demonstrate that citizen science can provide estimates of seabird colony arrival and departure that are comparable to 'expert' data extraction. This method has several advantages over traditional field methods, including reduced cost, less disturbance, potential to cover a much larger geographical area, provision of standardized estimates across regions and increase in societal engagement in seabird monitoring. We found that at higher latitudes, adult Kittiwakes return to the colony to breed later and depart later at the end of the breeding season, in line with previous studies. However, at one site, birds appeared to return to the colony during winter – an

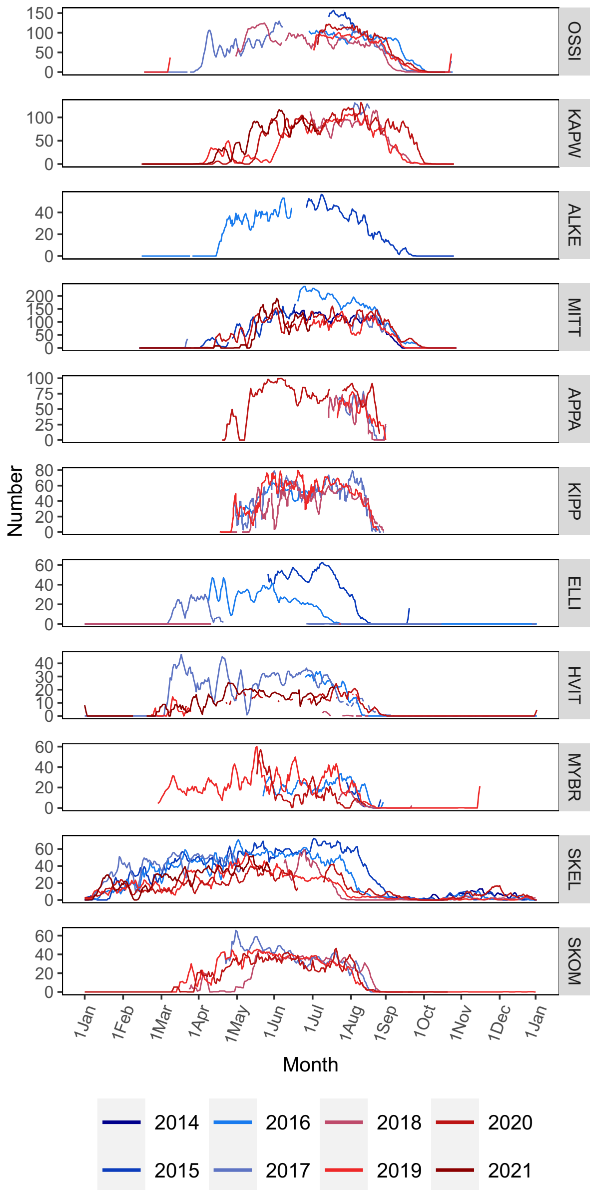

Figure 5. Number of adult Kittiwakes (smoothed using a 5-day moving average) counted from citizen science consensus classifications for each day of the year, in different years. Colonies are arranged in latitudinal order: OSSI = Ossian Sarsfjellet, KAPW = Kapp Waldberg, ALKE = Alkhornet, MITT = Midterhukfjellet, APPA = Appársuit, KIPP = Kippaku, ELLI = Elliðaey, HVIT = Hvítabjarnarey, MYBR = Mykines, SKEL = Skellig Michael, SKOM = Skomer.

observation not previously detected there because of observer visits only occurring in the breeding season – suggesting regional differences in Kittiwake over-winter behaviour.

Camera set-up

The Kittiwake camera network has allowed the collection of an enormous quantity of data (> 200 000 images) from 2014 to the present. Time-lapse cameras have enabled monitoring at a large spatiotemporal scale, in infrequently monitored locations, and harsh environments, applying a standardized methodology to facilitate comparison across sites.

Maintaining such an extensive camera network is not without its challenges, especially in coastal environments in winter, where strong winds, waves and precipitation can knock cameras over, obscure camera lenses or cause camera failure (e.g. water ingress; Merkel *et al.* 2016). As a result, the network contains gaps in data, where either cameras have failed or images are unusable, for example because they are blurred or the birds are obscured (e.g. condensation, precipitation on the lens). Furthermore, problems arising in winter are rarely identified until the following spring when fieldwork resumes. Remote image transmission could help overcome this problem, as images would be viewable online year-round, and issues with data capture could be identified and prioritized. Installing two cameras per colony could also increase the network's resilience, as if one camera fails, images would still be available from the other camera. Although this would increase cost in the short-term, cameras are comparatively cheap (c.£800 per camera and mount) compared with in-person field monitoring, especially when travel to remote islands is required and fieldworkers must be present regularly throughout the breeding season (Huffeldt & Merkel 2013, Merkel *et al.* 2016). Although this study only tested the use of citizen science image analysis for measuring colony arrival and departure, the camera network also has the potential to answer questions about the possible drivers of change in seabird breeding phenology, success and chick survival, provided data can be efficiently analysed (Hinke *et al.* 2018, Black *et al.* 2018b, Youngflesh *et al.* 2021).

Citizen science data validation

The *Zooniverse* platform engages > 1.6 million registered users worldwide, who can participate in over 50 active projects that span a range of disciplines, from astronomy to ecology, to help analyse large datasets (Cox *et al.* 2015). Creating a *Zooniverse*

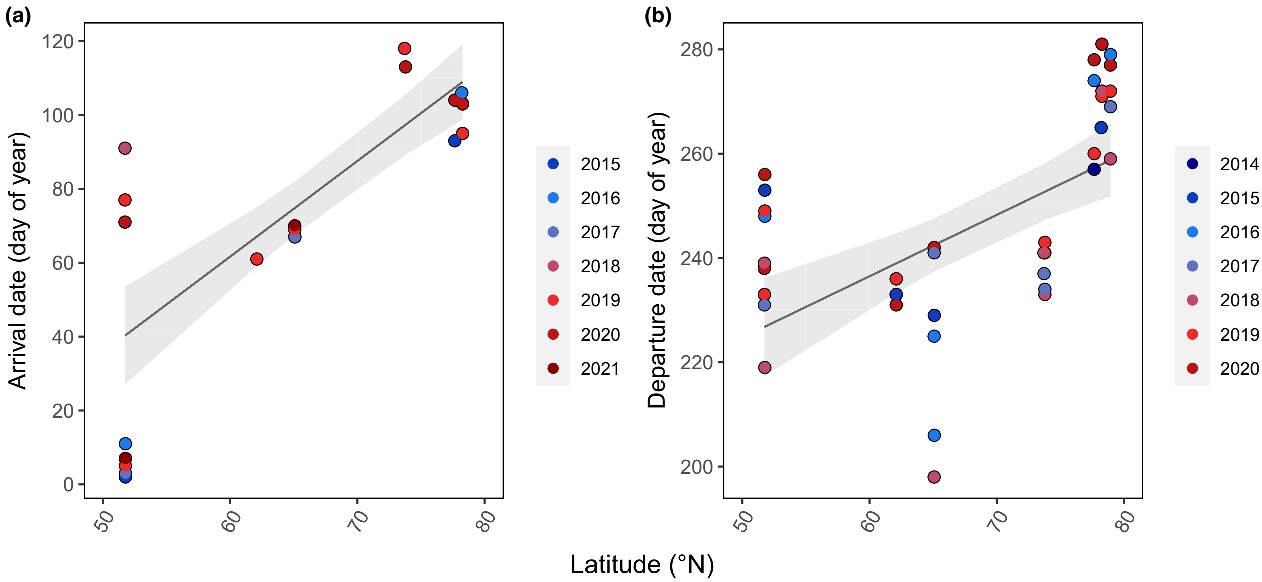

Figure 6. Relationship between latitude and Kittiwake colony arrival date (n = 22) (a) and departure date (n = 40) (b), with standard error (grey shading). Arrival was 2.6 (se = ±0.71) days later per 1° increase in latitude ($t(18)$ = 3.66, P < 0.01), and departure was 1.2 (se = ±0.49) days later per 1° increase in latitude ($t(36)$ = 2.42, P < 0.05).

project is free of cost, as development of the platform is funded by awards and grants (e.g. from the Alfred P. Sloan Foundation) (www.zooniverse.org). This makes the total monetary cost of the combined camera and citizen science system greatly reduced compared with other seabird monitoring techniques, such as traditional field observations and tagging, for the number of birds monitored.

When appropriate clustering and moving averages were applied, citizen science and 'expert' data showed no significant differences in phenological parameters routinely used to determine responses to environmental change. This demonstrates how large citizen science datasets can answer important ecological questions with similar confidence to 'expert' analysis, but at greater scales. Measuring colony-level arrival and departure with moving averages, rather than recording arrival and departure of birds at individual nests, removes the need for citizen science consensus classifications to accurately identify every bird in each image, provided the general trends of increase and decrease are present.

This study did not compare citizen science measures of phenology with those measured using 'traditional' field methods. This is because fieldworkers are rarely present when adult Kittiwakes first arrive at the colony (median arrival date 12 March) or when they leave (median departure date 29 August), as most fieldwork programmes are focused on the core breeding season, from egg-laying to chick fledging (Walsh *et al.* 1995). Future *Seabird Watch* studies aiming to measure additional breeding parameters, such as breeding success, will need to compare citizen science, 'expert' image analysis and fieldworker identification of chicks and resultant metrics, where possible. Validation is crucial in the development of all novel and emerging technologies, to show that resultant data are equivalent to (or better than) the existing approach.

Citizen scientist participation and retention

For citizen science data to be integrated into monitoring programmes, it must reduce researcher workload and be capable of consistently collecting data in the long-term. The time required by volunteers to annotate images depends on the number of birds per image (affected by camera location/position, time of year, time of day), number of species present and the number of life-stages present (e.g. adults and/or chicks). *Seabird Watch* images are presented to users at random, meaning that these factors should vary across a series of images examined, which can help to retain volunteer interest. When two researchers annotated a random selection of images, they averaged 1.2 min per image (researcher 1 completed 42 images in 60 min; researcher 2 completed 60 images in 60 min). This means that volunteers have saved c.1740 h (over 10 months, if working a 40-h week) of researcher image processing time, for the c.87000 images classified using the 'Timelapse' workflow to date.

However, to provide long-term monitoring solutions, citizen science projects also need to have enough volunteers in the long-term. Over the past 6 years, the 'Timelapse' workflow has maintained sufficient volunteer effort (median number of images classified per month was 3700, IQR 2003–9576) to process the new images collected each year. Volunteer participation was highest during the first month of the project (Fig. 3a), when it was featured on the UK TV programme *Autumnwatch* (https://www.bbc.co.uk/programmes/b0079t1) and peaked again during the COVID-19 pandemic, like many other *Zooniverse* projects (Ibrahim *et al.* 2021). Although participation has been sustained, the retention of individual volunteers was far less than expected. Most volunteers classified fewer than 10 images (median 5, IQR 2–12) in a single day (median number of days 0, IQR 0–0), and subsequently did not participate again. Similar volunteer patterns have been found for other *Zooniverse* projects, suggesting that it is much harder to maintain volunteer interest than it is to recruit new volunteers (Sauermann & Franzoni 2015, Crall *et al.* 2017). In the long-term, this could affect the accuracy of data generated, as volunteers do not have time to learn and improve their classifications; although for this study, high turnover does not appear to have been an issue, as citizen science and 'expert' phenology dates were comparable.

Hosting our project on a well-known and long-established citizen science platform has probably helped maintain a steady flow of new volunteers, particularly when *Seabird Watch* was 'featured' on the *Zooniverse* homepage (different projects are chosen to be featured each week, by the *Zooniverse* team) (Crall *et al.* 2017). Equally, promoting the project on other platforms, such as SciStarter (https://scistarter.org/) and Twitter/X (https://twitter.com), has helped recruit people (Crall *et al.* 2017). Rewarding volunteers for their efforts might encourage long-term participation (West & Pateman 2016), and *Seabird Watch* already provides volunteer certificates for a range of community engagement recognition programmes. Introducing competitive elements between volunteers, such as ranking and badging systems, can be rewarding (Robinson *et al.* 2021), as can receiving personal feedback from the project (e.g. via system-generated, but editable, emails) (Pecl *et al.* 2019). Regular project updates, and the opportunity to interact with the researchers, as well as other volunteers, can likewise ensure that volunteers know their contributions are valued and allow them to feel part of a wider community (West & Pateman 2016, Robinson *et al.* 2021). Increased use of the *Seabird Watch* Talk function by both researchers and volunteers could promote this.

Increasingly, machine learning and artificial intelligence are being used for image object detection to reduce image processing time and provide long-term data processing solutions (Christin *et al.* 2019, Borowiec *et al.* 2022, Pichler & Hartig 2023). Large training datasets are typically needed to train a model to recognize the objects of interest, and citizen science image annotations can provide such datasets, given that they are sufficiently accurate (Jones *et al.* 2020).

To date, artificial intelligence has predominantly been used to identify adult seabirds in drone and time-lapse images, but very few studies have attempted to identify seabird chicks (Jones *et al.* 2020, Hayes *et al.* 2021, Kellenberger *et al.* 2021, Weinstein *et al.* 2022). This might be because small chicks are difficult to detect when they first hatch, as they are often brooded by a parent (Coulson 2011). Chick appearance then changes significantly as they grow-up, until they often look completely different just before fledging, which might make it hard to recognize the variable appearance of a (e.g. Kittiwake) chick as the same 'object' across time. Hentati-Sundberg *et al.* (2023) developed a video surveillance system combined with automated image processing to identify Common Guillemot *Uria aalge* adults, chicks and eggs and has been able to look at some aspects of nest attendance, breeding activity and phenology. The system was installed in a previously constructed artificial breeding cliff and uses five mains-powered cameras, mounted on five ledges to monitor c.23 pairs of Guillemots. As a result, the system is unlikely to be easily scalable, particularly in remote areas where reliable power is lacking. Specific camera set-ups can also impede the generalizability of neural networks, as models trained on a particular image set may not be able to make accurate predictions when faced with novel image sets (such as a different study site), even if they contain the same species. This means that models might have to be re-trained on new datasets, which increases computational time and costs, and requires further training data (Lamba *et al.* 2019). Citizen science annotations could provide such training data, which reiterates how citizen science and machine learning might complement each other to provide efficient and cost-effective image analysis techniques in the long-term.

Changes in arrival and departure with latitude

Using time-lapse cameras and citizen science annotations, we showed that Kittiwake colony arrival was 2.6 days later per 1° increase in latitude from 51.7°N to 78.9°N. This is in line with previous research using traditional in-person monitoring showing that seabird breeding (namely average lay and/or hatching date) occurs later with increasing latitude at both the global (Keogan *et al.* 2018, 2022) and regional (Wanless *et al.* 2009, Burr *et al.* 2016) scale. Baker (1939) predicted a 2- to 3-day delay in egg-laying for every 1° increase in latitude, and Burr *et al.* (2016) found Kittiwake hatching was delayed by 2.3 days per latitudinal degree from 65°N to 79°N. Importantly, our result fits into this range of a 2- to 3-day delay per degree of latitude, showing that the novel methodology used here can detect known ecological patterns. The methodology can further be used to measure inter-annual variation in phenology, as cameras can provide long time-series of data. This is important for trying to understand the drivers of phenological change, and how environmental conditions can affect populations through breeding success and/or adult survival. The timing of arrival is of particular importance because it may affect the timing of breeding and subsequent reproductive success, and departure to the wintering grounds may consequently affect adult survival or cause potential carry-over effects the following breeding season.

In our study, we also expected departure to be delayed with latitude (because a later start should mean a later finish) and found this to be true, with a delay of 1.2 days per 1° latitudinal increase. The smaller magnitude delay in departure (1.2 days) relative to arrival (2.6 days) supports studies showing that breeding season length is shorter at latitudinal extremes, although we did not have sufficient data to test this directly (Hodum 2002, Burr *et al.* 2016). At one of the lowest latitude sites, Skellig Michael, small numbers of Kittiwakes were present between October and December, despite most of the colony leaving by mid-September, post-breeding. This supports previous studies showing that Kittiwakes breeding around the Celtic–Biscay shelf (Rathlin, 55°N and Skomer 52°N; Frederiksen *et al.* 2012) (Rockabill 54°N; SEAPOP 2023) tend to remain near the colony year-round, and do not necessarily migrate to the West Atlantic during winter like most other Kittiwake populations (Frederiksen *et al.* 2012). Nevertheless, we did not observe Kittiwakes in 1:00 PM images from Skomer between September 2019 and February 2020, suggesting that birds remaining near the colony do not always visit breeding sites during winter. Further research is needed on the occurrence and reasons for over-winter colony attendance in Kittiwakes. Winter visitors might be young birds practising at establishing nests, adults maintaining a pair bond (Harris & Wanless 1989) or adults competing for nests, with winter attendance being more likely at locations where competition for high-quality nest-sites is intense (Bennett *et al.* 2022). Our time-lapse camera and citizen science system represents a powerful tool to study such attendance patterns, given the lack of traditional field observations during winter.

CONCLUSIONS

In this study, we demonstrate how large-scale camera networks can measure phenological changes at remote colonies over a large geographical range, in a species of high conservation concern, and that this could be applied to cliff-nesting seabirds more widely. The potential to measure additional phenological parameters (such as chick hatch and chick fledge dates), nest survival and productivity, at comparatively low cost (Black 2018) is high. Long-term maintenance of such camera networks and robust methods for analysing large quantities of images, such as citizen science, are essential if we hope to address temporal trends and explore how reproduction is affected by key drivers of environmental change.

This publication uses data generated via the Zooniverse platform, development of which is funded by generous support, including a Global Impact Award from Google, and by a grant from the Alfred P. Sloan Foundation. The research was further supported by a Natural Environment Research Council DTP studentship (grant NE/S007474/1 to AJE), as well as individual contributions to Seabird Watch, particularly through donations during Quark Expeditions' voyages. We would like to thank Quark Expeditions and reserve wardens for assistance with fieldwork logistics, as well as the Zooniverse team and Seabird Watch volunteers, without whom this project would not be possible. We are also grateful to anonymous reviewers who provided valuable feedback on the manuscript.

AUTHOR CONTRIBUTIONS

Alice J. Edney: Writing – original draft; formal analysis; conceptualization; writing – review and editing; funding acquisition; data curation. **Jóhannis Danielsen:** Writing – review and editing; resources. **Sébastien Descamps:** Writing – review and editing; resources. **Jón Einar Jónsson:** Writing – review and editing; resources. **Ellie Owen:** Writing – review and editing; supervision; resources; funding acquisition. **Flemming Merkel:** Writing – review and editing; resources. **Róbert A. Stefánsson:** Writing – review and editing; resources. **Matt J. Wood:** Writing – review and editing; supervision; resources; funding acquisition. **Mark J. Jessopp:** Writing – review and editing; supervision; resources; conceptualization; funding acquisition. **Tom Hart:** Writing – review and editing; supervision; resources; conceptualization; funding acquisition.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

FUNDING

Natural Environment Research Council.

ETHICAL NOTE

None.

Data Availability Statement

The data that support the findings of this study are available in the Supporting Information of this article.

REFERENCES

Baker, J.R. 1939. The relation between latitude and breeding seasons in birds. *Proc. Zool. Soc. London* **A108**: 557–582.

Bates, D., Mächler, M., Bolker, B. & Walker, S. 2015. Fitting linear mixed-effects models using lme4. *J. Stat. Softw.* **67**: 1–48.

Bennett, S., Harris, M.P., Wanless, S., Green, J.A., Newell, M.A., Searle, K.R. & Daunt, F. 2022. Earlier and more frequent occupation of breeding sites during the non-breeding season increases breeding success in a colonial seabird. *Ecol. Evol.* **12**: e9213.

BirdLife International. 2023. *Species factsheet: Rissa tridactyla*. Available at: http://www.birdlife.org (accessed 27 March 2023).

Black, C.E. 2018. Spying on seabirds: a review of time-lapse photography capabilities and limitations. *Seabird* **31**: 1–14.

Black, C., Rey, A.R. & Hart, T. 2017. Peeking into the bleak midwinter: investigating nonbreeding strategies of Gentoo Penguins using a camera network. *Auk* **134**: 520–529.

Black, C., Southwell, C., Emmerson, L., Lunn, D. & Hart, T. 2018a. Time-lapse imagery of Adélie penguins reveals differential winter strategies and breeding site occupation. *PLoS One* **13**: e0193532.

Black, C., Collen, B., Lunn, D., Filby, D., Winnard, S. & Hart, T. 2018b. Time-lapse cameras reveal latitude and season influence breeding phenology durations in penguins. *Ecol. Evol.* **8**: 8286–8296.

Bolton, M., Butcher, N., Sharpe, F., Stevens, D. & Fisher, G. 2007. Remote monitoring of nests using digital camera technology. *J. Field Ornithol.* **78**: 213–220.

Bonter, D.N. & Cooper, C.B. 2012. Data validation in citizen science: a case study from project FeederWatch. *Front. Ecol. Environ.* **10**: 305–307.

Borowiec, M.L., Dikow, R.B., Frandsen, P.B., McKeeken, A., Valentini, G. & White, A.E. 2022. Deep learning as a tool for ecology and evolution. *Methods Ecol. Evol.* **13**: 1640–1660.

Burr, Z.M., Varpe, Ø., Anker-Nilssen, T., Erikstad, K.E., Descamps, S., Barrett, R.T., Bech, C., Christensen-Dalsgaard, S., Lorentsen, S., Moe, B., Reiertsen, T.K. & Strøm, H. 2016. Later at higher latitudes: large-scale variability in seabird breeding timing and synchronicity. *Ecosphere* **7**(5). Portico. https://doi.org/10.1002/ecs2.1283

Burthe, S., Daunt, F., Butler, A., Elston, D., Frederiksen, M., Johns, D., Newell, M., Thackeray, S. & Wanless, S. 2012. Phenological trends and trophic mismatch across multiple levels of a North Sea pelagic food web. *Mar. Ecol. Prog. Ser.* **454**: 119–133. https://doi.org/10.3354/meps09520

Christin, S., Hervet, É. & Lecomte, N. 2019. Applications for deep learning in ecology. *Methods Ecol. Evol.* **10**: 1632–1644.

Coulson, J. 2011. *The Kittiwake*. London, UK: T. and A.D. Polser.

Cox, J., Oh, E.Y., Simmons, B., Lintott, C., Masters, K., Greenhill, A., Graham, G. & Holmes, K. 2015. Defining and measuring success in online citizen science: a case study of Zooniverse projects. *Comput. Sci. Eng.* **17**: 28–41.

Crall, A., Kosmala, M., Cheng, R., Brier, J., Cavalier, D., Henderson, S. & Richardson, A. 2017. Volunteer recruitment and retention in online citizen science projects using marketing strategies: lessons from season spotter. *JCOM* **16**: A01.

Croxall, J.P., Butchart, S.H.M., Lascelles, B., Stattersfield, A.J., Sullivan, B., Symes, A. & Taylor, P. 2012. Seabird conservation status, threats and priority actions: a global assessment. *Bird Conserv. Int.* **22**: 1–34.

Descamps, S., Ramírez, F., Benjaminsen, S., Anker-Nilssen, T., Barrett, R.T., Burr, Z., Christensen-Dalsgaard, S., Erikstad, K.-E., Irons, D.B., Lorentsen, S.-H., Mallory, M.L., Robertson, G.J., Reiertsen, T.K., Strøm, H., Varpe, Ø. & Lavergne, S. 2019. Diverging phenological responses of Arctic seabirds to an earlier spring. *Glob. Chang. Biol.* **25**: 4081–4091.

Dickinson, J.L., Zuckerberg, B. & Bonter, D.N. 2010. Citizen science as an ecological research tool: challenges and benefits. *Annu. Rev. Ecol. Evol. Syst.* **41**: 149–172.

Dickinson, J.L., Shirk, J., Bonter, D., Bonney, R., Crain, R.L., Martin, J., Phillips, T. & Purcell, K. 2012. The current state of citizen science as a tool for ecological research and public engagement. *Front. Ecol. Environ.* **10**: 291–297.

Edney, A.J. 2020. *Development of Time-Lapse Photography for the Population Monitoring of a Colonial Seabird*. Masters thesis, University of Gloucestershire.

Edney, A.J. & Wood, M.J. 2021. Applications of digital imaging and analysis in seabird monitoring and research. *Ibis* **163**: 317–337.

Edney, A.J., Hart, T., Jessopp, M.J., Banks, A., Clarke, L.E., Cugnière, L., Elliot, K.H., Juarez Martinez, I., Kilcoyne, A., Murphy, M., Nager, R.G., Ratcliffe, N., Thompson, D.L., Ward, R.M. & Wood, M.J. 2023. Best practices for using drones in seabird monitoring and research. *Mar. Ornithol.* **51**: 265–280.

Foster-Smith, J. & Evans, S.M. 2003. The value of marine ecological data collected by volunteers. *Biol. Conserv.* **113**: 199–213.

Frederiksen, M., Harris, M.P., Daunt, F., Rothery, P. & Wanless, S. 2004. Scale-dependent climate signals drive breeding phenology of three seabird species. *Glob. Chang. Biol.* **10**: 1214–1221.

Frederiksen, M., Moe, B., Daunt, F., Phillips, R.A., Barrett, R.T., Bogdanova, M.I., Boulinier, T., Chardine, J.W., Chastel, O., Chivers, L.S., Christensen-Dalsgaard, S., Clément-Chastel, C., Colhoun, K., Freeman, R., Gaston, A.J., González-Solís, J., Goutte, A., Grémillet, D., Guilford, T., Jensen, G.H., Krasnov, Y., Lorentsen, S.-H., Mallory, M.L., Newell, M., Olsen, B., Shaw, D., Steen, H., Strøm, H., Systad, G.H., Thórarinsson, T.L. & Anker-Nilssen, T. 2012. Multicolony tracking reveals the winter distribution of a pelagic seabird on an ocean basin scale. *Divers. Distrib.* **18**: 530–542.

Gorleri, F.C., Jordan, E.A., Roesler, I., Monteleone, D. & Areta, J.I. 2022. Using photographic records to quantify accuracy of bird identifications in citizen science data. *Ibis* **165**: 458–471.

Harris, M.P. & Wanless, S. 1989. Fall colony attendance and breeding success in the common Murre. *Condor* **91**: 139–146.

Hayes, M.C., Gray, P.C., Harris, G., Sedgwick, W.C., Crawford, V.D., Chazal, N., Crofts, S. & Johnston, D.W. 2021. Drones and deep learning produce accurate and efficient monitoring of largescale seabird colonies. *Ornithol. Appl.* **123**: 1–16.

Hentati-Sundberg, J., Olin, A.B., Reddy, S., Berglund, P., Svensson, E., Reddy, M., Kasarareni, S., Carlsen, A.A., Hanes, M., Kad, S. & Olsson, O. 2023. Seabird surveillance: combining CCTV and artificial intelligence for monitoring and research. *Remote Sens. Ecol. Conserv.* **9**(4): 568–581. Portico. https://doi.org/10.1002/rse2.329

Hertzog, L.R., Frank, C., Klimek, S., Röder, N., Böhner, H.S. & Kamp, J. 2021. Model-based integration of citizen science data from disparate sources increases the precision of bird population trends. *Divers. Distrib.* **27**: 1106–1119.

Hinke, J.T., Barbosa, A., Emmerson, L.M., Hart, T., Juáres, M.A., Korczak-Abshire, M., Milinevsky, G., Santos, M., Trathan, P.N., Watters, G.M. & Southwell, C. 2018. Estimating nest-level phenology and reproductive success ofcolonial seabirds using time-lapse cameras. *Methods Ecol. Evol.* **9**: 1853–1863.

Hipfner, J.M. 2008. Matches and mismatches: ocean climate, prey phenology and breeding success in a zooplanktivorous seabird. *Mar. Ecol. Prog. Ser.* **368**: 295–304.

Hodum, P.J. 2002. Breeding biology of high-latitude Antarctic fulmarine petrels (Procellariidae). *J. Zool.* **256**: 139–149.

Huffeldt, N.P. & Merkel, F.R. 2013. Remote time-lapse photography as a monitoring tool for colonial breeding seabirds: a case study using thick-billed Murres (*Uria lomvia*). *Waterbirds* **36**: 330–341.

Ibrahim, K., Khodursky, S. & Yasseri, T. 2021. Gender imbalance and spatiotemporal patterns of contributions to citizen science projects: the case of Zooniverse. *Front. Phys.* **9**: 650720.

Jäckel, D., Mortega, K.G., Darwin, S., Brockmeyer, U., Sturm, U., Lasseck, M., Moczek, N., Lehmann, G.U.C. & Voigt-Heucke, S.L. 2023. Community engagement and data quality: best practices and lessons learned from a citizen science project on birdsong. *J. Ornithol.* **164**: 233–244.

Johnston, D.T., Furness, R.W., Robbins, A.C., Tyler, G.A. & Masden, E.A. 2019. Camera traps reveal predators of breeding Black Guillemots *Cepphus grille*. *Seabird* **32**: 72–83.

Jones, F.M., Allen, C., Arteta, C., Arthur, J., Black, C., Emmerson, L.M., Freeman, R., Hines, G., Lintott, C.J., Macháčková, Z., Miller, G., Simpson, R., Southwell, C., Torsey, H.R., Zisserman, A. & Hart, T. 2018. Time-lapse imagery and volunteer classifications from the Zooniverse Penguin Watch project. *Sci. Data* **5**: 180124.

Jones, F.M., Arteta, C., Zisserman, A., Lempitsky, V., Lintott, C.J. & Hart, T. 2020. Processing citizen science and machine-annotated time-lapse imagery for biologically meaningful metrics. *Sci. Data* **7**: 1–15.

Kellenberger, B., Veen, T., Folmer, E. & Tuia, D. 2021. 21 000 birds in 4.5 h: efficient large-scale seabird detection with machine learning. *Remote Sens. Ecol. Conserv.* **7**: 445–460.

**Keogan, K., Daunt, F., Wanless, S., Phillips, R.A., Walling, C.A., Agnew, P., Ainley, D.G., Anker-Nilssen, T., Ballard, G., Barrett, R.T., Barton, K.J., Bech, C., Becker, P., Berglund, P.-A., Bollache, L., Bond, A.L., Bouwhuis, S., Bradley, R.W., Burr, Z.M., Camphuysen, K., Catry, P., Chiaradia, A., Christensen-Dalsgaard, S., Cuthbert, R., Dehnhard, N., Descamps, S., Diamond,

T., Divoky, G., Drummond, H., Dugger, K.M., Dunn, M.J., Emmerson, L., Erikstad, K.E., Fort, J., Fraser, W., Genovart, M., Gilg, O., González-Solís, J., Granadeiro, J.P., Grémillet, D., Hansen, J., Hanssen, S.A., Harris, M., Hedd, A., Hinke, J., Igual, J.M., Jahncke, J., Jones, I., Kappes, P.J., Lang, J., Langset, M., Lescroël, A., Lorentsen, S.-H., Lyver, P.O., Mallory, M., Moe, B., Montevecchi, W.A., Monticelli, D., Mostello, C., Newell, M., Nicholson, L., Nisbet, I., Olsson, O., Oro, D., Pattison, V., Poisbleau, M., Pyk, T., Quintana, F., Ramos, J.A., Ramos, R., Reiertsen, T.K., Rodríguez, C., Ryan, P., Sanz-Aguilar, A., Schmidt, N.M., Shannon, P., Sittler, B., Southwell, C., Surman, C., Svagelj, W.S., Trivelpiece, W., Warzybok, P., Watanuki, Y., Weimerskirch, H., Wilson, P.R., Wood, A.G., Phillimore, A.B. & Lewis, S. 2018. Global phenological insensitivity to shifting ocean temperatures among seabirds. *Nat. Clim. Chang.* **8**: 313–318.

Keogan, K., Daunt, F., Wanless, S., Phillips, R.A., Alvarez, D., Anker-Nilssen, T., Barrett, R.T., Bech, C., Becker, P.H., Berglund, P.-A., Bouwhuis, S., Burr, Z.M., Chastel, O., Christensen-Dalsgaard, S., Descamps, S., Diamond, T., Elliott, K., Erikstad, K.-E., Harris, M., Hentati-Sundberg, J., Heubeck, M., Kress, S.W., Langset, M., Lorentsen, S.-H., Major, H.L., Mallory, M., Mellor, M., Miles, W.T.S., Moe, B., Mostello, C., Newell, M., Nisbet, I., Reiertsen, T.K., Rock, J., Shannon, P., Varpe, Ø., Lewis, S. & Phillimore, A.B. 2022. Variation and correlation in the timing of breeding of North Atlantic seabirds across multiple scales. *J. Anim. Ecol.* **91**: 1797–1812.

Knudson, T.W., Lovvorn, J.R., Lawwon, M.J., Corcoran, R.M., Roby, D.D., Piatt, J.F. & Pyle, W.H. 2020. Can oceanic prey effects on growth and time to fledging mitigate terrestrial predator limitation of an at-risk seabird? *Ecosphere* **11**: e0322.

Kobori, H., Dickinson, J.L., Washitani, I., Sakurai, R., Amano, T., Komatsu, N., Kitamura, W., Takagawa, S., Koyama, K., Ogawara, T. & Miller-Rushing, A.J. 2016. Citizen science: a new approach to advance ecology, education, and conservation. *Ecol. Res.* **31**: 1–19.

Krawczyk, C., Langley, A., Amyrebecca, Allen, C., McMaster, A. & Wolfenbarger, Z. 2022. *zooniverse/aggregation-for-caesar: Version 4.0.0*. Zenodo. https://doi.org/10.5281/zenodo.6979588

Lamba, A., Cassey, P., Segaran, R.R. & Koh, L.P. 2019. Deep learning for environmental conservation. *Curr. Biol.* **29**: R977–R982.

Merkel, F.R., Johansen, K.L. & Kristensen, A.J. 2016. Use of time-lapse photography and digital image analysis to estimate breeding success of a cliff-nesting seabird. *J. Field Ornithol.* **87**: 84–95.

Mitchell, P.I. & Parsons, M. 2007. *Strategic Review of the UK Seabird Monitoring Programme*. JNCC Unpubl. Rep.

Moe, B., Stempniewicz, L., Jakubas, D., Angelier, F., Chastel, O., Dinessen, F., Gabrielsen, G., Hanssen, F., Karnovsky, N., Rønning, B., Welcker, J., Wojczulanis-Jakubas, K. & Bech, C. 2009. Climate change and phenological responses of two seabird species breeding in the high-Arctic. *Mar. Ecol. Prog. Ser.* **393**: 235–246.

Møller, A.P., Rubolini, D. & Lehikoinen, E. 2008. Populations of migratory bird species that did not show a phenological response to climate change are declining. *Proc. Natl Acad. Sci. USA* **105**: 16195–16200.

Paleczny, M., Hammill, E., Karpouzi, V. & Pauly, D. 2015. Population trend of the world's monitored seabirds, 1950–2010. *PLoS One* **10**: e0129342.

Pascalis, F., Collins, P. & Green, J. 2018. Utility of time-lapse photography in studies of seabird ecology. *PLoS One* **13**: e0208995.

Pecl, G.T., Stuart-Smith, J., Walsh, P., Bray, D.J., Kusetic, M., Burgess, M., Frusher, S.D., Gledhill, D.C., George, O., Jackson, G., Keane, J., Martin, V.Y., Nursey-Bray, M., Pender, A., Robinson, L.M., Rowling, K., Sheaves, M. & Moltschaniwskyj, N. 2019. Redmap Australia: challenges and successes with a large-scale citizen science-based approach to ecological monitoring and community engagement on climate change. *Front. Mar. Sci.* **6**: 349. https://doi.org/10.3389/fmars.2019.00349

Phillips, R.A., Fort, J. & Dias, M.P. 2023. Conservation status and overview of threats to seabirds. In Young, L. & VanderWerf, E. (eds) *Conservation of Marine Birds*: 33–56. Cambridge, MA: Academic Press.

Pichler, M. & Hartig, F. 2023. Machine learning and deep learning—a review for ecologists. *Methods Ecol. Evol.* **14**: 994–1016.

R Core Team 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. Available at: https://www.R-project.org/ (accessed 31 March 2023).

Raddick, M.J., Bracey, G., Gay, P.L., Lintott, C.J., Murray, P., Schawinski, K., Szalay, A.S. & Vandenberg, J. 2010. Galaxy zoo: exploring the motivations of citizen science volunteers. *Astron. Educ. Rev.* **9**: 10103.

Regular, P.M., Hedd, A., Montevecchi, W.A., Robertson, G.J., Storey, A.E. & Walsh, C.J. 2014. Why timing is everything: energetic costs and reproductive consequences of resource mismatch for a chick-rearing seabird. *Ecosphere* **5**: 1–13.

Richards, C., Cooke, R.S.C. & Bates, A.E. 2021. Biological traits of seabirds predict extinction risk and vulnerability to anthropogenic threats. *Glob. Ecol. Biogeogr.* **30**: 973–986.

Robinson, J.A., Kocman, D., Speyer, O. & Gerasopoulos, E. 2021. Meeting volunteer expectations — a review of volunteer motivations in citizen science and best practices for their retention through implementation of functional features in CS tools. *J. Environ. Plan. Manag.* **64**: 2089–2113.

Sauermann, H. & Franzoni, C. 2015. Crowd science user contribution patterns and their implications. *Proc. Natl Acad. Sci. USA* **112**: 679–684.

Sauve, D., Divoky, G. & Friesen, V.L. 2019. Phenotypic plasticity or evolutionary change? An examination of the phenological response of an arctic seabird to climate change. *Funct. Ecol.* **33**: 2180–2190.

SEAPOP. 2023. SEATRACK. Available at: https://seapop.no/en/seatrack/ (accessed 28 March 2023).

Shultz, M.T., Piatt, J.F., Harding, A.M.A., Kettle, A.B. & Van Pelt, T.I. 2009. Timing of breeding and reproductive performance in murres and kittiwakes reflect mismatched seasonal prey dynamics. *Mar. Ecol. Prog. Ser.* **393**: 247–258.

Southwell, C. & Emmerson, L. 2015. Remotely-operating camera network expands Antarctic seabird observations of key breeding parameters for ecosystem monitoring and management. *J. Nat. Conserv.* **23**: 1–8.

Swanson, A., Kosmala, M., Lintott, C. & Packer, C. 2016. A generalized approach for producing, quantifying, and validating citizen science data from wildlife images. *Conserv. Biol.* **30**: 520–531.

Thackeray, S.J., Sparks, T.H., Frederiksen, M., Burthe, S., Bacon, P.J., Bell, J.R., Botham, M.S., Brereton, T.M., Bright, P.W., Carvalho, L., Clutton-Brock, T., Dawson, A., Edwards, M., Elliott, J.M., Harrington, R., Johns, D., Jones, I.D., Jones, J.T., Leech, D.I., Roy, D.B., Scott, W.A., Smith, M., Smithers, R.J., Winfield, I.J. & Wanless, S. 2010. Trophic level asynchrony in rates of phenological change for marine, freshwater and terrestrial environments. *Glob. Chang. Biol.* **16**: 3304–3313.

Thackeray, S.J., Henrys, P.A., Hemming, D., Bell, J.R., Botham, M.S., Burthe, S., Helaouet, P., Johns, D.G., Jones, I.D., Leech, D.I., Mackay, E.B., Massimino, D., Atkinson, S., Bacon, P.J., Brereton, T.M., Carvalho, L., Clutton-Brock, T.H., Duck, C., Edwards, M., Elliott, J.M., Hall, S.J.G., Harrington, R., Pearce-Higgins, J.W., Høye, T.T., Kruuk, L.E.B., Pemberton, J.M., Sparks, T.H., Thompson, P.M., White, I., Winfield, I.J. & Wanless, S. 2016. Phenological sensitivity to climate across taxa and trophic levels. *Nature* **535**: 241–245.

Viola, B.M., Sorrell, K.J., Clarke, R.H., Corney, S.P. & Vaughan, P.M. 2022. Amateurs can be experts: a new perspective on collaborations with citizen scientists. *Biol. Conserv.* **274**: 109739.

Waldron, A., Mooers, A.O., Miller, D.C., Nibbelink, N., Redding, D., Kuhn, T.S., Roberts, J.T. & Gittleman, J.L. 2013. Targeting global conservation funding to limitimmediate biodiversity declines. *Proc. Natl Acad. Sci. USA* **110**: 12144–12148.

Walsh, P.M., Halley, D. & Harris, M.P. 1995. *A compilation of methods for survey and monitoring of breeding seabirds*: 168. Peterborough: JNCC.

Wanless, S., Frederiksen, M., Walton, J. & Harris, M.P. 2009. Long-term changes in breeding phenology at two seabird colonies in the western North Sea. *Ibis* **151**: 274–285.

Weinstein, B.G., Garner, L., Saccomanno, V.R., Steinkraus, A., Ortega, A., Brush, K., Yenni, G., McKellar, A.E., Converse, R., Lippitt, C.D., Wegmann, A., Holmes, N.D., Edney, A.J., Hart, T., Jessopp, M.J., Clarke, R.H., Marchowski, D., Senyondo, H., Dotson, R., White, E.P., Frederick, P. & Morgan Ernest, S.K. 2022. A general deep learning model for bird detection in high resolution airborne imagery. *Ecol. Appl.* **32**: e2694.

West, S. & Pateman, R. 2016. Recruiting and retaining participants in citizen science: what can be learned from the volunteering literature? *Citiz. Sci. Theory Pract.* **1**: 1–10.

Whelan, S., Hatch, S.A., Gaston, A.J., Gilchrist, H.G. & Elliott, K.H. 2022. Opposite, but insufficient, phenological responses to climate in two circumpolar seabirds: relative roles of phenotypic plasticity and selection. *Funct. Ecol.* **36**: 1782–1795.

Youngflesh, C., Jones, F.M., Lynch, H.J., Arthur, J., Ročkaiová, Z., Torsey, H.R. & Hart, T. 2021. Large-scale assessment of intra- and inter-annual breeding success using a remote camera network. *Remote Sens. Ecol. Conserv.* **7**: 97–108.

Received 31 March 2023;
Revision 31 January 2024;
revision accepted 15 February 2024.
Associate Editor: Arjun Amar.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Boxplots and paired dot plots comparing the (a) arrival and (b) departure dates derived from citizen science consensus classifications (grey) and researcher analysis (white).

Table S1. Available *Seabird Watch* data that have been annotated on the *Zooniverse* platform, for sites used in this analysis.

Table S2. Results of paired samples Wilcoxon tests comparing the arrival and departure dates derived from citizen science consensus classifications and researcher analysis.

Table S3. Kittiwake colony arrival dates measured for each colony using citizen science consensus classifications.

Table S4. Kittiwake colony departure dates measured for each colony using citizen science consensus classifications.