Drones, automatic counting tools and artificial neural networks in wildlife population censusing

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Drones, automatic counting tools and artificial neural networks in wildlife population censusing

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Abstract

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3. The automatic counting birds was best done with the microbiology software - ImageJ / Fiji: the average bird counting rate was 100 birds in 82 seconds.
4. Machine learning using neural network algorithms proved to be an effective and fast way of counting birds – 100 birds in 23 seconds. However, as the preparation of images and machine learning time are time-consuming, this method is recommended only for large data sets and large bird assemblages.
5. The responsible study of wildlife using a drone should only be carried out by persons experienced in the biology and behaviour of the animals concerned.

Introduction

Biological diversity conservation has become, next to dealing with the consequences of climate change, one of the most important challenges for humanity (Díaz et al. 2006). The total loss of some species and the rapid decline of others has taken on a so far unknown dynamic (Hooper et al. 2012). Some species will probably not be described at all before they become extinct (Costello et al. 2013). Therefore, we should make every effort to use new technological solutions in ecological research in such a way that the knowledge gained with their use can be effectively used in nature conservation (Arts et al. 2015). In a rapidly changing world, we need ecological research methods that are fast, effective and minimally invasive. In consequence, we will be able to dynamically react to negative changes in the environment (Díaz-Delago et al. 2017).

Large vertebrates, especially birds, have been considered indicators of the state of the environment (Amat & Green 2010). Many long-term bird monitoring programmes have been established in many places around the world (e.g. Farina et al. 2011, Reif 2013, Niemi et al. 2016). New initiatives are constantly emerging, and as a result of this ever denser network of research programmes, we are acquiring an increasingly precise model of ecological processes on Earth (Gregory & Strien 2010). To meet this challenge, we need new, more effective methods and tools.

With regard to modern techniques of gathering ecological data, we are starting to face analytical issues (Shin & Choi 2015) comparable to those in other fields, such as microbiology or biochemistry. Using the principle of similarities of natural structures, such as the similarities of a river network to a blood vessel network (e.g. LaBarbera & Rosso 1989; Neagu & Bejan 1999), I found that waterbird colonies could be construed as bacterial colonies. Since software is commonly used for counting microorganisms, it has been tested many times and its precision confirmed (Barbedo 2012). In the case of aerial photos, it seems justified to use analytical methods previously reserved for areas such as microbiology, such as the ImageJ open software platform used for automatic object counting (Schindelin et al. 2012) or Passing Bablok regression, used to compare methods in clinical laboratory work (Bilić-Zulle 2011).

The use of Unmanned Aerial Vehicles (hereafter drones) in ecological research has already been described in research on breeding (e.g. Chabot et al. 2015; Ratcliffe et al. 2015) and non-breeding birds (e.g. Hodgson et al. 2018; Jarrett et al. 2020), as well as marine (e.g. Koski et al. 2015; Adame et al. 2017) and terrestrial mammals (Vermeulen et al. 2013; Hu et al. 2020). This has turned out to be an effective method for studying larger vertebrates, mainly birds and mammals, but also reptiles (Elsey & Trosclair 2016), as well as for other ecological studies (Puttock et al. 2015; Michez et al. 2016). Nonetheless, research using drones is still at an early stage, and further studies are needed to establish both methodological standards and the actual effectiveness of working with this tool (Barnas et al. 2020). Apart from efficiency and time saving, an important issue is the invasiveness of this method and the safety of the studied object. Initial research in this area has already been carried out on a limited group of species (e.g. Vas et al. 2015; Jarrett et al. 2020).

Waterbirds are a special group of animals, as they often make use of hard-to-reach habitats, such as islands in water bodies or wetlands. Being bioindicators of environmental quality, they are also a frequent object of monitoring studies (Amat & Green 2010; Amano et al. 2017). Therefore, the use of a drone for research on this group of animals should be doubly beneficial: 1) easy and quick access to hard-to-reach areas, and 2) limited disturbance of birds – there is no need to enter a breeding colony or disturb a flock.

The objective of this research was to assess the extent to which the above assumptions were correct. I focused on the effectiveness of a population censusing method using a drone, its invasiveness, the automated analysis of the data obtained by the drone, and the application of Artificial Intelligence (AI) for interpreting the results. The field study was carried out on colonial breeding waterbirds and gregarious waterbirds forming flocks during the non-breeding period. I selected various species that occupy different habitats: these can be divided into four categories – open water, arable fields and meadows, wetlands and islets.

My research questions were: 1) Will it be possible/safe to count nests / incubating birds / individuals using a drone over a colony or a flock? 2) Will the appearance of a drone over the breeding colony or flock cause the birds to react and, if so, what kind of reaction takes place? 3) Is automatic counting using dedicated software and Machine Learning applicable to bird censusing?

Methods

Study area and species

The study was carried out on colonial and gregarious species of waterbirds in northern Poland (Europe). Most of the observations were made in the lower course and estuary of a large lowland river – the Lower Oder Valley (site-centre location in decimal degrees: Longitude - 14.413200, Latitude - 53.085000). The observations were made in areas known for their importance for waterbirds, during the breeding season, migration, and the wintering period. (Ławicki et al. 2010, Marchowski et al. 2018).

The study covered a total of 33 species of waterbirds, including 15 breeding and 28 non-breeding species. The responses of 10 species to the drone in both the breeding and non-breeding periods were compared.

Table 1. List of species surveyed using a drone.

No.	Species	Breeding	Non-breeding
1	Mute Swan *Cygnus olor*	Y	Y
2	Whooper Swan *Cygnus cygnus*	N	Y
3	Greater White-fronted Goose *Anser albifrons*	N	Y
4	Bean Goose *Anser fabalis/serrirostris**	N	Y
5	Greylag Goose *Anser answer*	Y	Y
6	Mallard *Anas platyrhynchos*	Y	Y
7	Northern Pintail *Anas acuta*	N	Y
8	Eurasian Teal *Anas crecca*	N	Y
9	Eurasian Wigeon *Mareca penelope*	N	Y
10	Gadwall *Mareca strepera*	Y	Y
11	Pochard *Aythya ferina*	N	Y
12	Greater Scaup *Aythya marila*	N	Y
13	Tufted Duck *Aythya fuligula*	N	Y
14	Common Scoter *Melanitta nigra*	N	Y
15	Long-tailed Duck *Clangula hyemalis*	N	Y
16	Common Goldeneye *Bucephala clangula*	N	Y
17	Goosander *Mergus merganser*	N	Y
18	Red-breasted Merganser *Mergus serrator*	N	Y
19	Great Crested Grebe *Podiceps cristatus*	Y	Y
20	Great Cormorant *Phalacrocorax carbo*	N	Y
21	Grey Heron *Ardea cinerea*	Y	Y
22	Great Egret *Ardea alba*	N	Y
23	Eurasian Coot *Fulica atra*	N	Y
24	Common Crane *Grus grus*	Y	Y
25	Black-headed Gull *Chroicocephalus ridibundus*	Y	Y
26	Common Gull *Larus canus*	Y	Y
27	Mediterranean Gull *Ichthyaetus melanocephalus*	Y	N
28	*Larus argentatus sensu lato***	Y	Y
29	Great Black-backed Gull *Larus marinus*	N	Y
30	Little tern *Sternula albifrons*	Y	N
31	Common Tern *Sterna hirundo*	Y	N
32	Black Tern *Chlidonias niger*	Y	N
33	Whiskered Tern *Chlidonias hybrida*	Y	N

* Bean Goose complex (two species Tundra and Taiga Bean Goose

Anser fabalis/serrirostris.

** The group of closely related large gulls in the study area are Herring Gull *Larus argentatus* and Caspian Gull *Larus cachinnans.*

Inventory using a drone

A DJI Phantom drone (version 4 Pro V2.0) was used for the fieldwork. This is a remotely controlled quadcopter device with a total weight of 1,388 grams, equipped with a camera capable of taking both still photographs (max quality 5,472x3,648 pixels) and videos (max quality: 4,096 x 2,160 pixels), with the possibility of continuous tracking of unrecorded images transmitted to the display coupled with the remote control. Each photo records the geographic location and altitude in the metadata.

A drone flight was performed over sites where birds were known to be regularly present (Ławicki et al. 2010; Marchowski et al. 2018). The distance from the observer to these sites was usually several hundred metres, but never less than 100 m. This precluded any influence on the part of the observer on the birds' behaviour. But if birds were scared away as a result of the observer's presence, no attempt was made to fly the drone. The flight height was set at about 100 m – the same as recommended for bird counts from aircraft (Meissner 2011). From this height, the planned census area was scanned for birds. If a flock or individual birds were spotted on the remote controller display, a photo was taken, and the birds were approached. Up to a height of 30 m, birds were approached diagonally in such a way that the height and distance from the birds were about the same. After reaching 30 m (when the birds were still not responding to the drone), the drone was moved over the birds, the distance was shortened while the height was maintained, after which the drone was lowered to about 10 m. The birds' reactions (if the terrain permitted them to be seen) were recorded by a second observer using a spotting scope mounted on a tripod. The birds' reactions were also monitored in real time via the display on the drone's remote controller. The behaviour of the birds was observed on a sample plot of approximately 40,000 m^2 (200 x200 m), but if the site was smaller (e.g. a small lake, pool or islet), the entire site was treated as a sample plot.

My main research question was whether it would be possible/safe to conduct bird research using a drone. How do birds react to a drone: do they ignore it, attack it, or does the drone flush them? The birds' reactions to the drone were first divided into two basic categories: reaction – no reaction. In the reaction category, the following subcategories were created: the birds 1 – moved slowly away, 2 – dived, 3 – were flushed over a short distance but remained in the sample plot, or quickly returned, 4 – were scared away, exhibited a panic reaction, left the sample plot and did not return, 5 – attacked the drone.

Reactions 4 and 5 were placed in an "unfavourable" category, i.e. where the study of birds using a drone would not be recommended. No reaction and non-invasive reactions (1-3) were placed in a separate category. Statistical significance was tested using the chi-square goodness of fit. The statistical analyses were carried out using the software program R (R Core Team. 2021).

The second aim was to test the ability to count birds in non-breeding aggregations or nests in breeding colonies using a drone. After the initial recognition from a long distance of whether the birds were responding to the drone's presence, attempts were made to approach the colony, with photos being taken continuously. If it was noticed that the drone had disturbed the birds in any way, it was recalled beyond the disturbing distance. The dates of drone flights over the breeding colonies were adjusted so as to take place when the colony was at the egg incubation stage. As a result, most of the nests present in the colony, represented by an incubating bird, were visible.

Colony or flock counting

The basic unit of the number of birds in a breeding colony is the breeding pair, represented by a nest or incubating bird. The analysis involves counting the incubating birds or, less frequently, the nests based on the photos taken by the drone. In non-breeding aggregations, all the individuals visible on a photo were counted.

Manual and semi-automatic counting

This involves printing an image of the colony, flock, or its part and then marking off the counted birds or nests. The marked birds / nests are grouped into tens; with larger colonies, supergroups multiplied by 10 are formed into sets of 100 nests / individuals.

Another approach is to use the object counting tool in Adobe Photoshop (Adobe Photoshop PS 2020: Image > Analysis > Count Tool). With this software, the clicks are counted automatically, with the consecutive number being displayed next to the clicked object.

A third method, also using Photoshop software, is to apply a layer to the counted object. This can be an ellipse or a rectangle with no filling. The layer is then duplicated and moved to the next object. When a layer is duplicated, a sequential copy number is assigned to it, so the last layer number plus one (first layer) gives the number of individuals in the count.

Automatic counting

One method of automatic counting uses the Adobe Photoshop (PS 2020) software tool for the automatic counting of objects (Image > Analysis > Select Data Points > Custom > Object Counting). The image needs to be prepared so that the software knows what to count. Using image processing tools such as Contrast, Brightness, Exposure and Threshold, the counted objects need to be exposed against the background. The best results are achieved when the objects to be counted can be seen against a completely uniform background. Then, using the Wand tool, the background is selected and the selection inverted. The next step is to open the Measurement Log and record the measurements. The software will automatically count the selected objects.

Another automatic counting method is the one used for counting microorganisms or cell structures – the Analyze Particles tool in the open-source Java image processing software – ImageJ (Grishagin 2015) and its and its extended version of Fiji (Schindelin et al. 2012).

Machine learning - neural network-based algorithm

This method was applied using the Fiji platform, the DenoiSeg tool from the CSBDeep plug-in, and the neural network algorithm for instance segmentation (Buchholz et al. 2020). The machine learning process requires an appropriate graphics card (e.g. NVIDIA) and the installation of several drivers and software that operate in the background of the main software (CUDA Toolkit, GPU support, TensorFlow, cuDNN SDK, Phyton etc.); they differ depending on the computer's firmware and operating system. After preparing the computer we need to manually prepare labelling images in the graphics software - photos enabling objects be sufficiently visible against the background. Then we need to pair them with the raw photos. To learn this neural network, a small number (2 - 10) of training data are needed. The most time-consuming aspects are the image preparation (training data) and the neural network learning process. Depending on the power of the computer, the latter may take a few, twelve or even more hours. This process produces a model that can be used for prediction (Buchholz et al. 2020; Schroeder et al. 2020). After running the model in Fiji software, cleaning the photo should take a few seconds, and then it should take only a few more seconds to count the birds using the Analyze Particles command in Fiji (Sandhya et al. 2011). The step-by-step procedure is described on the website devoted to this method, from which one can download sample data and perform the machine learning process on one's own computer: https://imagej.net/DenoiSeg

Comparison of counting methods

30 photos of bird assemblages were selected and analysed using different methods. A stopwatch was used to measure the time needed to process and count the birds. The Photoshop layers method allows one to zoom in on the image in order to check whether the bird should be added to the result. This enables the identification of species in a group and the activity performed by the bird (e.g. in a breeding colony, whether a bird is

incubating), i.e. information relevant to the interpretation of data (Fig. 1). Thus, the results obtained with this method were taken as reference values (proxy method). Then the count precision was compared with the proxy method using different methods.

Figure 1. Results of the Layers method: this permits a precise count of the birds incubating in a breeding colony, identification of the species, and activity, i.e., whether the bird is incubating or standing on the ground. Red circles - Black-headed Gulls incubating, black circles - Black-headed Gulls standing on the ground or in the water, yellow circles - Greylag Geese incubating and nest with eggs, blue circles – incubating Common Terns, white squares - birds with an unidentified activity, possibly dead.

A separate comparison of 43 images was used for the results obtained with the predictive machine learning model. The machine learning method requires additional assumptions and more preparatory work. 1) Images must be 8 bits. 2) The bird size needs to be roughly the same in all images, so downsizing is necessary using the resizing factor calculated from the image with the objects of the fewest pixels. 3) The images must be pseudo-normalized via automatic adjust brightness-contrast in Fiji software (Schindelin et al. 2012, Buchholz et al. 2020).

Passin Bablok Regression was used to compare the methods. This is a linear regression procedure with no special assumptions regarding sample distribution or measurement errors. The result does not depend on the assignment of the methods or instruments. The slope and intercept are calculated with their 95% confidence interval. These confidence intervals are used to determine whether there is only a chance difference between the slope and 1 and between the intercept and 0 (Passing & Bablok 1983, Bilić-Zulle 2011). The statistical analyses were carried out using the software program R (R Core Team. 2021).

If the methods were comparable (not significantly different) with the proxy method, the analysis execution time was compared in the next step.

Results

Reaction to the drone

The ratio of drone response to no response was almost half and half (52.8% - reaction, 47.2% - no reaction, chi-square test: $\chi 2 = 1.052$; $p = 0.30$, $n = 343$).

However, the drone-induced response was usually insignificant (birds moved slowly away or flew away for a short distance): most drone missions (84.8%) yielded a combination of no response and insignificant reactions. Significant reactions, i.e. birds being flushed from the sample plot or attacking the drone, together accounted for 15.2% (chi-square test: $\chi 2 = 10.828$; $p < 0.001$). This indicates that negligible (not significant for birds) reactions or none at all constitute the statistically significant majority (Table 2). The feasibility of counting birds using a drone was confirmed in 331 cases (n = 343, Table 2).

Table 2. Results of chi-square goodness of fit tests regarding the reaction of birds to the appearance of a drone. NAR = Non-acceptable response

Variable	n	n	%	%	The result of the goodness of fit test - chi-square
	0	1	0	1	
Drone reaction all species	0	343	0	100	-
Reaction NOT/YES	162	181	47.2	52.8	$\chi^2 = 1.053$; $p = 0.30$
NAR reaction NOT/YES	291	52	85.4	15.2	$\chi^2 = 10.83$; $p < 0.001$ ***
Count possible	0	343	0	100	-
NOT/YES	12	331	3.5	96.5	$\chi^2 = 15.14$; $p < 0.001$ ***

Unacceptable reactions (flushing from the sample plot or attack on the drone) occurred in 52 cases. The average distance from the drone to the birds when this type of reaction occurred was 35.8 m (± min.-max. 15 m – 50 m). In the case of breeding birds, an unacceptable reaction took place in three cases (n = 83) and involved only one species – Black Tern *Chlidonias niger* ; the reaction was an attempted attack on a drone. In the case of non-breeding birds, unacceptable reactions occurred in 49 cases (n = 260), all of them involving the birds flying off beyond the sample plot. None of the non-breeding birds attempted to attack the drone. The average flock size among birds displaying unacceptable reactions was 317 individuals and was slightly higher than among birds exhibiting no or negligible reactions (291).

Adverse (unacceptable) reactions were recorded in 13 species (n = 33). *Anser* geese were the most sensitive to the drone's presence with 35.8% of unacceptable reactions. Gulls were the least sensitive to the drone's presence: no unacceptable reactions were observed, and the birds were completely indifferent to the drone in 88.8% of cases (Table 3).

Table 3. The behaviour of birds in response to the drone, broken down into groups of similar species. Reaction codes: #0 – no reaction, #1 – slow movement away, #2 – diving, #3 – flushing over short distance flush, bird remained in the sample plot, or quickly returned, #4 – flushed, panic reaction, bird left the sample plot and did not return, #5 – attempted attack on the drone.

Group of species	No of obs.	%: code #0	%: code #1	%: code #2	%: code #3	%: code #4	%: code #5
Anser	65	41.5	9.2	0	13.8	**35.8**	**0**
Anas group*	24	41.6	37.5	0	12.5	**8.3**	**0**
Diving birds**	119	28.6	37.0	14.3	3.4	**16.8**	**0**
Gulls	36	88.8	5.6	0	5.6	**0**	**0**
Terns	28	75.0	3.8	0	10.7	**0**	**10.7**

*Ducks from the Anatini tribe consisted of the following genera:*Anas* , *Mareca* and *Spatula*

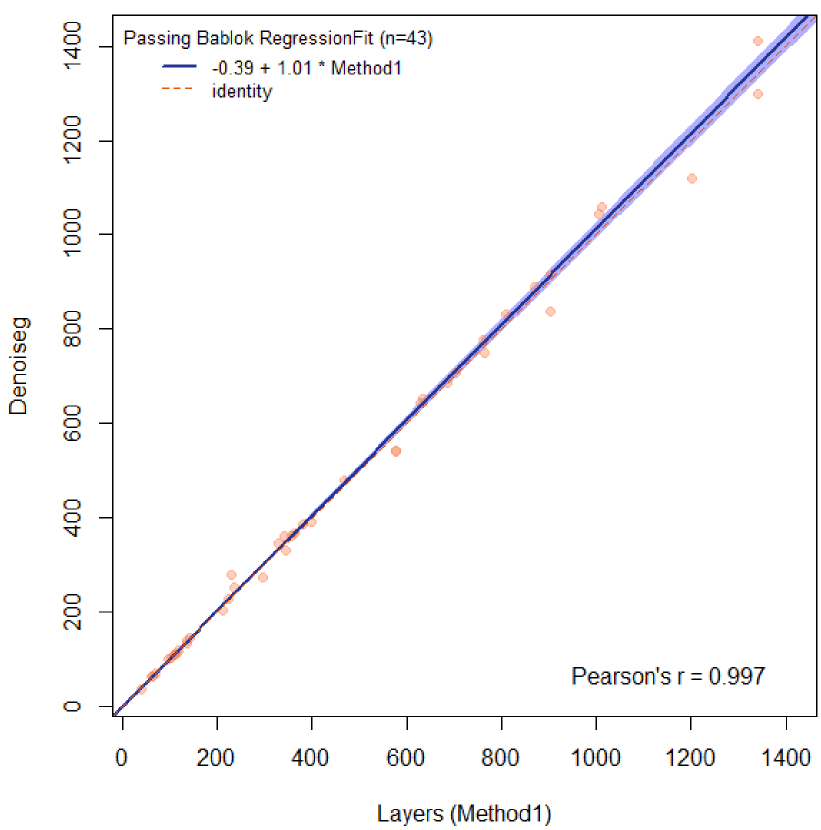
** Group consisting of diving ducks from the genera:*Aythya* , *Bucephala* , *Melanitta* , *Mergus* and*Clangula* , Coot *Fulica atra* , Great Crested Grebe*Podiceps cristatus* and Cormorant *Phalacrocorax carbo.*

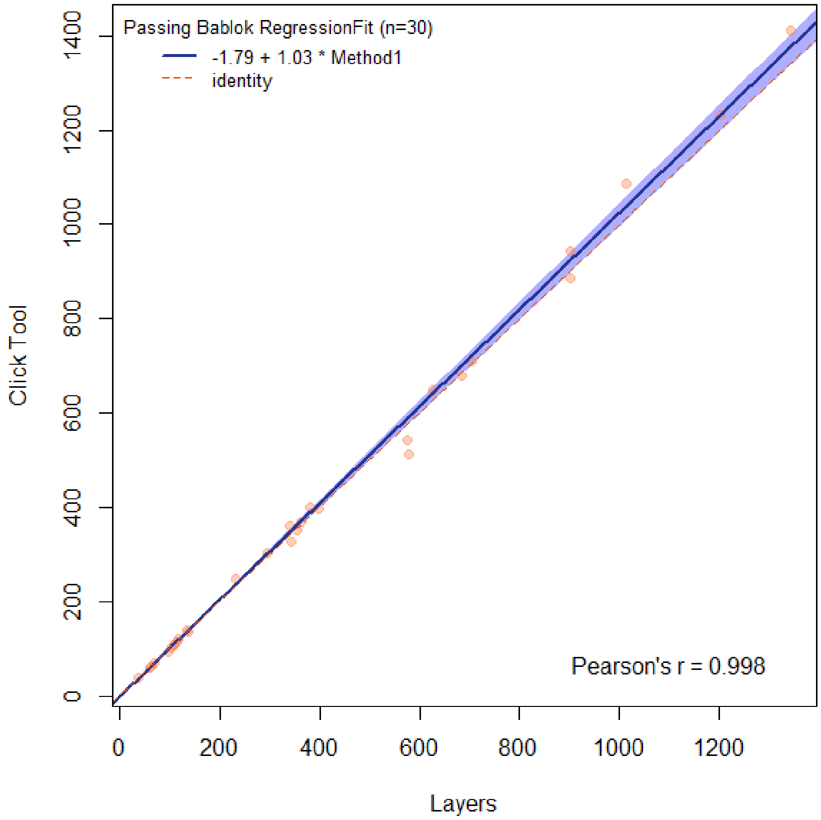
Comparison of counting methods

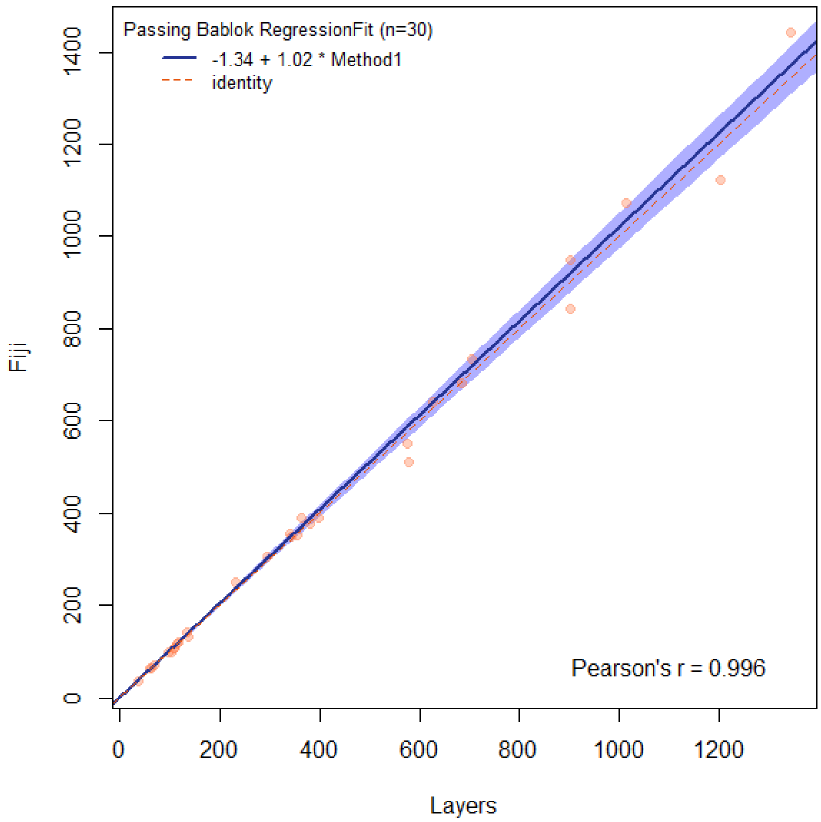
Confidence intervals of 95% (95%CI) explain whether the values differ from zero for the intercept and from 1 for the slope. For all methods except one – the Photoshop automatic count – 95% CI includes zero. Hence, there is no significant difference between the intercept value and the zero value, and there is no consistent difference between these methods. Likewise, if 95%CI for the slope includes the value one, there cannot be a significant difference between the slope and unity, and there is no proportional difference between the methods. As with the intercept, all the methods meet this assumption, except the Photoshop automatic count (Table 4, Fig.2).

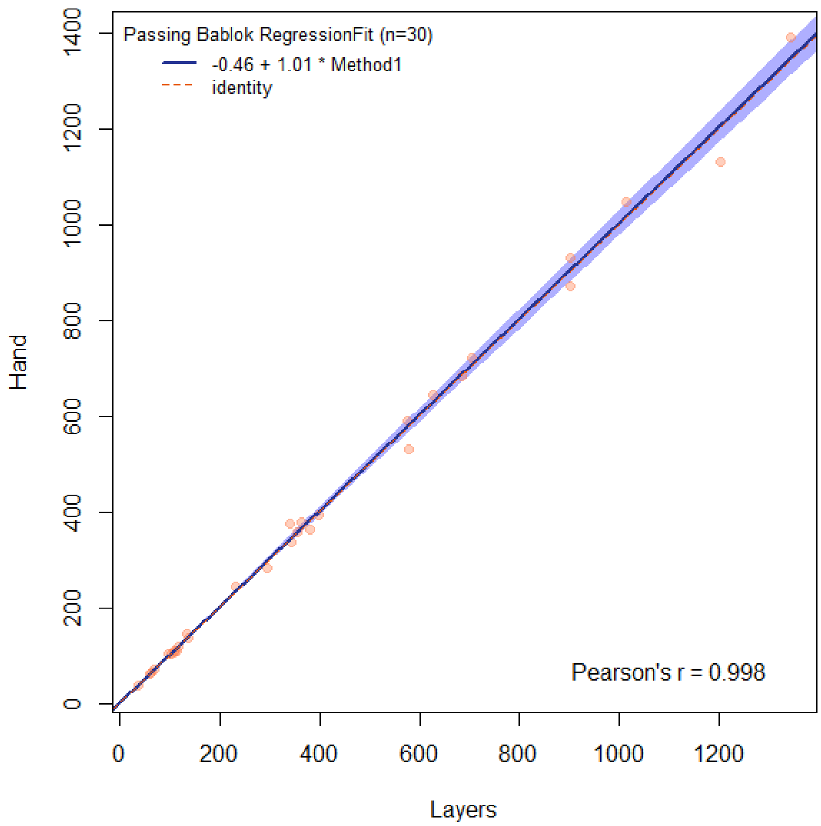
Table 4. Results of Passing Bablok regression models, comparison of counting methods.

Method comparison		Estimate	L 95%CI	U 95%CI
Layers vs Hand	Intercept	-0.4570928	-3.7818476	2.365561
	Slope	1.0052539	0.9767165	1.033742
Layers vs Fiji	Intercept	-1.340426	-6.0965405	4.691191
	Slope	1.021277	0.9723183	1.056719
Layers vs Photoshop autocount	Intercept	-310.98448	-1029.910211	-56.52771
	Slope	5.00817	3.965327	10.44304
Layers vs Click Tool	Intercept	-1.787051	-5.620580	0.5384848
	Slope	1.026672	0.997006	1.0484076
Layers vs Denoiseg	Intercept	-0.385159	-5.1828369	2.518013
	Slope	1.014134	0.9895461	1.031729




Passing Bablok RegressionFit (n=30)
-1.79 + 1.03 * Method1
identity
Pearson's r = 0.998
Click Tool
Layers
0
200
400
600
800
1000
1200
1400


Passing Bablok RegressionFit (n=30)
-1.34 + 1.02 * Method1
identity
Pearson's r = 0.996
Fiji
Layers
0
200
400
600
800
1000
1200
1400


Passing Bablok RegressionFit (n=30)
-0.46 + 1.01 * Method1
identity
Pearson's r = 0.998
Hand
Layers
0
200
400
600
800
1000
1200
1400

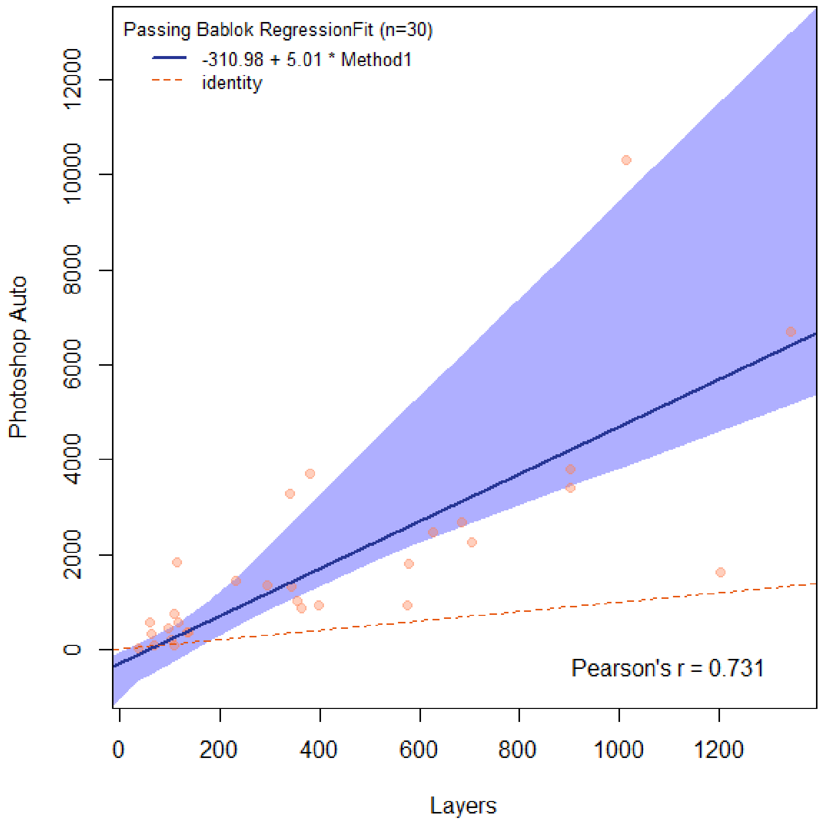


Fig. 2. Comparison of methods using Passing Bablok regression. The graphs show the observations with the regression line (solid line), the confidence interval for the regression line (dashed lines) and the identity line (x=y, dotted line). Comparison between the proxy methods and other methods: Denoiseg, Click Tool, Fiji, Hand and Photoshop Auto.

The Layers method was the most time-consuming, the average time needed to count 100 birds being 893 seconds. Birds were counted the fastest using the neural networks machine learning method (Denoiseg) – an average of 100 birds in 23 seconds. All methods except Denoiseg exhibited a significant correlation between the number of birds in the group and the time needed to count them: the more birds, the longer it took to count them. With the Denoiseg method, the number of individuals in a group did not affect the time needed to count them.

Table 5. Average time needed to count 100 individuals in a group of birds and correlation with the size of the group.

Method	Average time (seconds) to count 100 individuals	Pearson regression Time/number of ind.	Significance
Layers	893 (n=30)	0.969	p<0.001**
Hand	228 (n=30)	0.933	p<0.001**
Click Tool	217 (n=30)	0.891	p<0.001**
Fiji	82 (n=30)	0.562	p<0.001**

Method	Average time (seconds) to count 100 individuals	Pearson regression Time/number of ind.	Significance
Denoiseg	23 (n=43)	0.282	p=0.064

Discussion

Field study

The drone proved to be a useful tool for safely studying colonial and gregarious waterbirds: their flocks were counted in more than 96% of cases. It also turned out to be minimally invasive: out of 343 birds / missions, no dangerous event was recorded, such as a collision of a bird with the drone or a permanent nest abandonment as a result of a bird being scared away. A similar conclusion was reached during research conducted in Australia based on 97 flight hours (Lyons et al. 2018). The strongest reactions to the presence of the drone were displayed by*Anser* geese in the non-breeding period, mainly large flocks foraging on farmland. Similar results were obtained in Scotland, where, in addition, a dependence on flock size was demonstrated: the larger the flock, the greater the chance of its responding to a drone (Jarrett et al. 2020). Our results indicate that the group of birds reacting adversely to the drone was slightly larger than that exhibiting a moderate reaction or none at all. Birds in the non-breeding period reacted more strongly to the drone's appearance – 18.8% of adverse reactions. Breeding birds, on the other hand, appeared to be indifferent to the drone, undesirable behaviour being manifested in only 3 (3.6%) cases out of 83. Chabot et al. (2015) drew similar conclusions during their study in a Common Tern colony. In our case, however, these undesirable behaviours (observed in Black Tern) involved attempts to attack the drone. This is potentially more dangerous than when the birds are scared away over a long distance, as a bird-drone collision may ensue; drone attack behaviour has been reported in Australia (Lyons et al. 2018). Despite the positive results of this study, and the effectiveness and minimal invasiveness of the drone, the use of a drone for performing bird counts should be approached with great caution. The persons conducting the research must have a good knowledge of the study area, so that in the event of an emergency, the drone can be landed quickly. They must also be experienced in bird biology and behaviour in order to be able to predict and prevent dangerous situations.

The flushing of birds even at a long distance – behaviour No. 3 in this study, defined as unacceptable – may not have a significant effect on them, as they will probably return to the site after some time. But the effect of repeated drone flights may well be different, as this can lead to the permanent abandonment of a site. Therefore, the frequent flying of large numbers of drones over flocks of birds for recreational purposes should be proscribed. Drones are becoming more and more affordable (Kyrkou et al. 2019), and the temptation for people to "play" with birds will have a decidedly negative impact on the latter.

The present study was conducted by a person with 30 years of experience in field ornithology, so his ability to predict bird behaviour will have helped to avoid dangerous situations. At the present stage, of course, these are still speculations, but it is highly probable that people with less experience will pose a greater risk of dangerous situations for animals and other humans. Hence, the use of drones in wildlife research should be legally regulated: a license should be issued for such work, and the persons involved should have passed an examination in animal biology and behaviour.

Automatic counting

Bird counts using medic software have already been described by Pérez-García (2012), who used the UHT-SCSA Image Tool 3.0 software to perform a census of starlings. This software does not work everywhere, however: e.g. it cannot be installed in the Windows 10 operating system. Other free software dedicated to birds has been described by Descamps et al. (2011), who used this to count flamingos in breeding colonies. This latter software has turned out to be quite difficult to use: one serious difficulty is the use of French as the basic language and the inability to change the language version. In contrast, DotCount v1.2 is easy to use, but its disadvantage is the closed source, so that it cannot be used to create plugins or updates to enhance its functionality; moreover, the latest version of this stems from as long ago as 2012. In the future, the use of neural networks and machine learning in wildlife studies will undoubtedly increase in importance (e.g. Villa et al. 2017, Tabak et al. 2019). Clearly, there are many different possibilities and solutions for automatic bird counting, but at present, ImageJ / Fiji (Grishagin 2015) seems the best choice. It is an open-source platform, so several programmers and biologists can work together to create new plugins. Some of them already use neural network-based algorithms (Buchholz et al. 2020).

The automatic counting methods using the ImageJ / Fiji platform proved to be the best in our study, as they were the fastest and maintained the precision of the results (Tables 3 and 4, Fig. 2). For small and medium bird concentrations, we recommend using the Analyze Particles tool in the ImageJ / Fiji software program. This does require pre-treatment of each image each time, but with some practice, one can do this quite efficiently and the results will be precise.

In the case of solutions using neural network algorithms, a one-off count takes a very short time (23 seconds on average, Table 4), but to achieve this state requires a lot of prior preparation, and the images require some preliminary assumptions. The computer on which the machine learning will be conducted must have the appropriate hardware. Then the images have to be scaled in such a way that the objects are roughly the same size, and the learning time of the neural network can take up to several dozen hours. This method is therefore recommended in situations where a lot of data (images) have been acquired from long-term monitoring programmes, in large breeding colonies and in non-breeding concentrations.

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Author's contributions

D.M. is responsible for all parts of this work.

Data availability statement

The raw data on the basis of which the analyses were carried out are attached to the article as supplementary materials.

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