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Short communication

Automated monitoring for birds in flight: Proof of concept with eagles at a wind power facility

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ABSTRACT

Automated surveys for wildlife have the potential to improve data collection while averting mortality of animals. Collisions of eagles at wind power facilities are particularly of concern and therefore an automated system that could detect birds, determine if they are eagles, and track their movement, might aid in curtailing wind turbines before collisions occur. Here, we use human observers and photographs to test the ability of a camera-based monitoring system, called IdentiFlight, to detect, classify, and track birds. IdentiFlight detected 96% of the bird flights detected by observers and detected 562% more birds than did observers. The discrepancy between observers and IdentiFlight seemed to be because the ability of observers to detect birds declined sharply by distance and toward the west. We reviewed photographs taken by IdentiFlight and determined that IdentiFlight misclassified nine of 149 eagles as non-eagles for a false negative rate of 6%, and 287 of 1013 non-eagles as eagles for a false positive rate of 28%. The median distance at classification for birds classified as eagles was 793 m and the median time from detection till classification was 0.4 s. Collectively, our results suggest that automated cameras can be effective means of detecting birds in flight and identifying eagles.

1. Introduction

Wildlife management often requires assessing distribution, abundance, or movement of animals through space and time (Anderson et al., 2017; Williams et al., 2002). Such monitoring can be aided by automated technology, allowing researchers and managers to collect large amounts of data accurately and efficiently (Arts et al., 2015; August et al., 2015). For example, acoustic recordings are often used to monitor vocalizing birds (Shonfield and Bayne, 2017), and researchers can deploy camera traps to monitor a variety of taxa (Burton et al., 2015). Likewise, radar can be used to track migrating birds (Gauthreaux and Belser, 2003) and assess bird collision risk (e.g., Desholm and Kahlert, 2005; Gerringer et al., 2016; Jenkins et al., 2018).

The use of automated technology in applied ecology is increasing (Arts et al., 2015; August et al., 2015) alongside the need to detect and identify birds in flight. Collisions between birds and aircraft cause human fatalities and billions of dollars of damage each year (Allan and Orosz, 2001; Anderson et al., 2015; Sodhi, 2002), highlighting the importance of detecting and tracking birds to avoid collisions near airports (Gerringer et al., 2016). Bird collisions at wind power facilities are also a concern (Drewitt and Langston, 2006; Johnson et al., 2016; Loss et al., 2013; Smallwood, 2013; Watson et al., 2018), especially because fatalities may involve Bald (*Haliaeetus leucocephalus*) and Golden Eagles (*Aquila chrysaetos*), which are legally protected within the US (Bald and Golden Eagle Protection Act, 1940). Some wind power facilities employ people who watch for eagles from observation towers or other vantage points and order certain turbines to be powered down if eagles are deemed at risk of collision. The wind power industry might therefore benefit from an automated monitoring system that could detect, identify, and track eagles.

Past studies have used data collected by human observers (hereafter 'observers') to test the ability of acoustic recording units (Alquezar and Machado, 2015; Campos-Cerqueira and Aide, 2016; Leach et al., 2016) and radar (Dokter et al., 2013; Gerringer et al., 2016) to detect birds. These studies assume the automated system is useful if it detected a substantial proportion of birds detected by observers. Here, we use observers and photographs classified by an independent team of experts to test the ability of a camera-based monitoring system to detect birds in flight and determine whether they are eagles. We specifically examined the proportions of birds detected by one survey system (human or camera-based) but missed by the other. We also determined and

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compared the rates at which each system correctly classified birds as eagles or non-eagles. Finally, we calculated the distance at which the camera system detects birds and the time it required to determine if a bird is an eagle.

2. Methods

2.1. Study site

Duke Energy Renewable's Top of the World Windpower Project is a 200 MW project located ~14 km northeast of the town of Glenrock, Wyoming on ~17,000 acres of land. Top of the World Windpower Project is composed of 44 Siemens 2.3 MW, 101-meter rotor diameter wind turbines and 66 General Electric 1.5 MW, 82.5-meter rotor diameter wind turbines. All wind turbines at Top of the World have a hub height of 80 m above ground level. Activity of golden and bald eagles is high at Top of the World, and Duke Energy has been investing in strategies to reduce collision risk as part of its settlement agreement resulting from prosecution by the US Department of Justice (United States of America v. Duke Energy Renewables, 2013). Duke Energy installed four IdentiFlight units and asked the American Wind Wildlife Institute to provide an independent evaluation of the technology. Other bird species common within the study site that are of interest to airports and wind power facilities include Turkey Vultures (*Cathartes aura*), Red-tailed Hawks (*Buteo jamaicensis*), and Common Ravens (*Corvus corax*).

2.2. Field data collection

2.2.1. IdentiFlight

The IdentiFlight system (hereafter, IdentiFlight; Boulder Imaging, Boulder, Colorado) was developed to detect eagles at sufficient distance from wind turbines to determine in real-time whether any specific turbine or turbines should be shut down or prevented from starting. IdentiFlight is designed as a network of tower-mounted camera systems seven to 10-m-high. Each camera system (hereafter: 'IdentiFlight unit') consists of a ring of eight fixed Wide Field of View (WFOV) cameras and a High Resolution Stereo Camera (HRSC) mounted on a Pan and Tilt Unit (Fig. 1A). The WFOV cameras detect moving objects in the environment and begin to track them. Once a moving object is detected, the HRSC is pointed at the object. The HRSC estimates the line-of-sight distance to the object and takes photographs (Fig. 1C, D) every 200 ms (5/s) to gather the data necessary to classify the object as an eagle or non-eagle. Each IdentiFlight unit uses an algorithm to detect and classify objects within a 1000 m radius. See online appendix for further details of the classification algorithm and visual coverage of a given IdentiFlight camera system.

For this study, four tower mounted IdentiFlight units were deployed in a network along the northern ridgeline of Top of the World (Fig. 1B), a location within the project footprint that is known for eagle flight activity. Note that IdentiFlight units were not mounted on wind turbines, but on separate towers. The IdentiFlight towers were spaced between 530 and 630 m apart allowing for sufficient overlapping visual coverage (see online appendix, Fig. 1B).

2.2.2. Observers

Observers followed a point count survey methodology (i.e., point-based recording of activity) modified from Appendix C of USFWS (2013). On weekdays from 08 August–09 September 2016, observers conducted four 105-min point counts daily, with breaks between counts. The four counts occurred from 9:00–10:45, 11:00–12:45, 13:15–15:00, and 15:15–17:00 MST during all safe weather conditions and when visibility was > 800 m.

During each count, observers recorded all birds the size of an American Kestrel (*Falco sparverius*), or larger, seen within the defined 1000-m survey area, the time each individual bird entered and left their view or the survey area, and traced the path of the birds on an aerial map. Observers also estimated the height of the bird relative to themselves at detection and at its lowest and highest points. Whenever an observer lost sight of a bird (behind clouds, hills, etc.) then later appeared to regain sight of it, they would not count it as a different bird unless more than ~1 min had passed. We paired observers with IdentiFlight units so that each observer independently surveyed the same area covered by the associated unit. There were thus four concurrent surveys being conducted for each count period. Observers were rotated after each count to control for differences in observer skill. Surveys were conducted from vantage points where visibility was similar to that of the associated IdentiFlight unit. All observers were experienced in surveying for eagles.

2.3. Data processing

Our study design therefore consisted of four humans and four IdentiFlight units, each individually attempting to detect birds flying within a 1000-m radius. We combined the individual efforts of the IdentiFlight units and observers into composite records of all birds seen by each method during survey periods. The IdentiFlight output we examined for this study consisted of one image per second, along with bird spatial location coordinates, and the percent confidence in the classification decision (see online appendix for details) for each instance of an IdentiFlight unit detecting and tracking a bird. Because more than one IdentiFlight unit can detect and track the same individual bird, we combined records of flight paths if the start, end, or mid-point of any two flight paths from different IdentiFlight units were within 1 min in time and within 120 m in linear distance from each other. We chose the one-minute criterion to match the observer methods. The 120-m criterion was determined by IdentiFlight engineers as the maximum distance apart at which two flight paths might be considered the same bird. The primary intent was to minimize over-counting of individual birds, with the trade-off that birds flying close together in space and time would be under-counted.

To facilitate the processing of millions of images and data points, the manufacturer (Boulder Imaging) examined output from the IdentiFlight units and observers to pair the two datasets. For each bird detected by observers, Boulder Imaging determined whether the timing and flight path recorded by the observer overlapped flight paths recorded by IdentiFlight units (see online appendix for details). Boulder Imaging further determined which birds were detected by observers but did not correspond with any birds recorded by IdentiFlight, and vice versa.

We only report results for the 4-unit IdentiFlight system, as a whole, not for individual units because curtailment decisions will most likely be made based on the entire system and not individual units. We considered a bird to be classified by IdentiFlight as eagle or non-eagle based on the detection record from whichever IdentiFlight unit had the highest percent confidence in classification. If the highest-confidence detection was classified as an eagle, we considered the bird to be classified as an eagle. Likewise, if there were ties between detections for highest confidence, we deferred to detections classified as eagles. We further considered a bird to be identified as an eagle by observers if any observer classified the bird as an eagle.

We determined the accuracy with which IdentiFlight classified birds as eagles or non-eagles using the 1224 birds closer than 1000 m that were by both the observers and IdentiFlight. We contracted experienced raptor biologists to examine photographs associated with each of these birds and classified each bird as either eagle or non-eagle. Two raptor biologists scored each bird flight as either containing pictures of an eagle, or not. Where the two raptor experts differed in classification, a third biologist examined photographs to break the tie. Given the limited resources available to examine photographs, we did not examine photographs for birds that were not detected by humans.

We calculated time from detection until classification as the elapsed

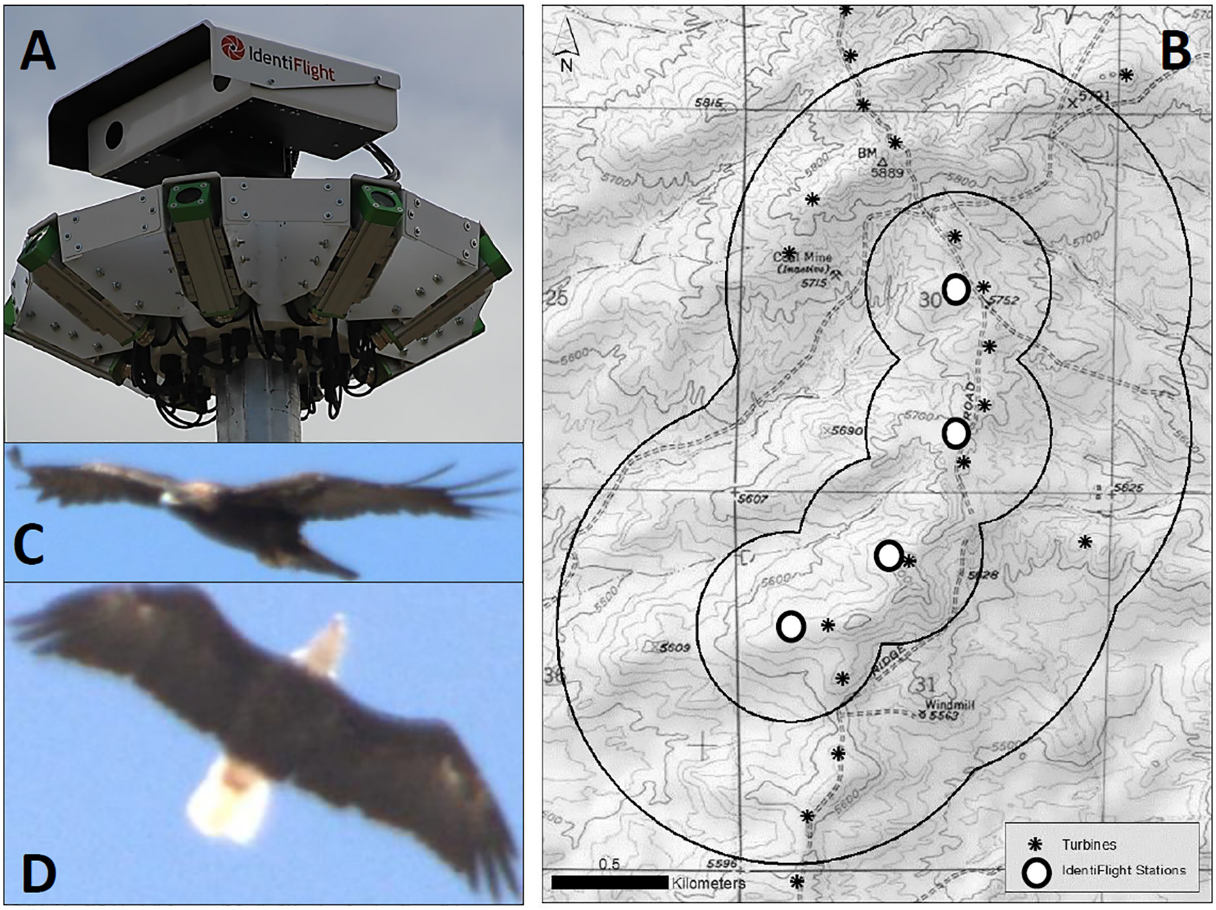

Fig. 1. A) IdentiFlight Camera System showing several of the Wide Field of View cameras and the High Resolution Stereo Camera mounted on a Pan and Tilt unit. B) Map of the study site with 1-km (the combined zone of visual coverage, outer polygon) and 400-m (inner polygon) buffers shown around IdentiFlight units. C) Photograph of a Golden Eagle that was taken and correctly classified by IdentiFlight. D) Photograph of a Bald Eagle that was taken and correctly classified by IdentiFlight.

time from the first instance of detection by IdentiFlight until classification was made by the IdentiFlight unit that had the highest percent confidence classification. We further determined the distance from the nearest IdentiFlight unit at the time classification was made by the IdentiFlight unit that had the highest percent confidence classification. Although IdentiFlight is designed to operate within 1000 m, it detected some birds beyond this distance ($n = 770$) and those detections were included in the distance and time analyses.

2.4. Analysis

Treating the identification from the photographs as truth, we calculated true positive rate, or 'sensitivity'—the probability that an eagle is correctly identified as an eagle—and true negative rate, or 'specificity'—the probability that a non-eagle is correctly classified as a non-eagle (sensu Fielding and Bell, 1997). Using the R (R Core Team, 2016) package DTComPair (Stock and Hielscher, 2014), we calculated sensitivity and specificity (and corresponding standard errors) of observers and IdentiFlight using the acc.paired() function, and compared the rates of both systems using McNemar's test (McNemar, 1947). We also determined whether error rates (false negative and false positive) for observers and IdentiFlight were correlated with the minimum distance a bird was estimated to be from an IdentiFlight tower using logistic regression (1 = error, 0 = correct classification, McClure et al., 2012a).

We further investigated the potential factors that might cause observers to miss birds that were detected by IdentiFlight. We built a series of logistic regression models using all subsets of a global model that contained covariates hypothesized to affect detection rates as independent variables and whether a bird that was detected by IdentiFlight was also detected by observers as the dependent variable (1 = detected, 0 = missed). We hypothesized that the horizontal and direct (i.e., line-of-sight) distance, vertical angle and height above the observer, and compass direction might affect the probably that an observer would detect a bird. Because vertical angle and height above the observer ($r = -0.74$) and vertical and horizontal distance ($r = 0.96$) were highly correlated, we only included directionality, horizontal distance, and height above the IdentiFlight tower in the global model. None of the parameters in the global model were highly correlated ($r < 0.28$; Graham, 2003). For each bird flight, we used the values calculated at the point where the classification of eagle or non-eagle was made by IdentiFlight. To examine directionality we sine and cosine transformed the compass direction from the IdentiFlight tower that made the classification to create measures of 'eastness' and 'northness', respectively. We ranked and compared all models using Akaike's Information Criterion (Akaike, 1974) corrected for small sample size (AICc, Hurvich and Tsai, 1989) then model-averaged across the entire model set (Burnham and Anderson, 2002) using the AICcmodavg package (Mazerolle, 2011) in R. We considered parameters to be useful for inference if the model-averaged 95% confidence interval excluded zero. Using the package ROCR (Sing et al., 2005), we calculated the Area under the Receiver Operating Curve (AUC, Fielding and Bell, 1997; Pearce and Ferrier, 2000; Zweig and Campbell, 1993) for the global model as a measure of model fit (McClure et al., 2012b; Seavy and Alexander, 2011). Following, Pearce and Ferrier (2000), we

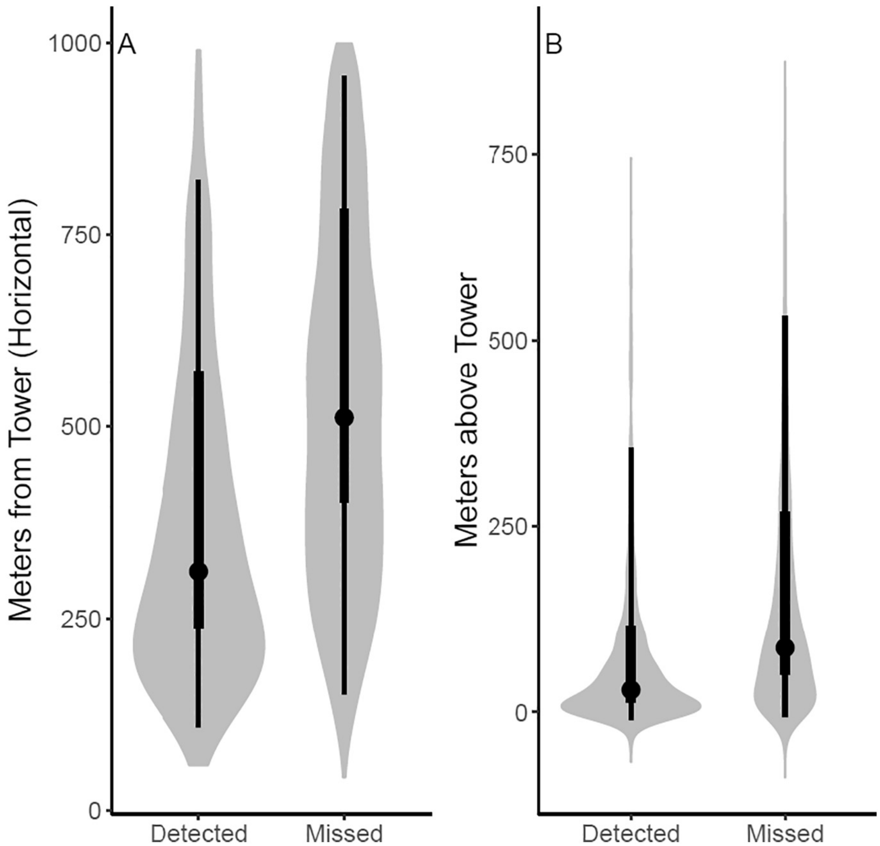

Fig. 2. Relationship between Horizontal (A) and Vertical (B) distance from the nearest IdentiFlight unit for birds detected by IdentiFlight and detected by observers ("Detected"; $n = 1224$) or missed by observers ("Missed"; $n = 5958$). Gray shading represents violin plots of positions where individual birds were classified as either eagle or non-eagle IdentiFlight. Black points represent medians, thick solid lines represent the 34th and 84th percentiles (which represent ± 1 SD under a normal distribution), and thin black lines represent 2.5th and 97.5th percentiles.

considered the global model to be useful if AUC was > 0.7.

3. Results

3.1. Detection

Observers detected 1277 birds flying through the IdentiFlight survey area (≥10 m above the observers and within 1000 m). Of those birds, IdentiFlight detected 96%, missing 53 birds. Four of the missed birds were classified as eagles by observers. On two of those occasions there were two eagles flying together and the system classified them as a single eagle. Another missed eagle was being harassed by a hawk, causing the system to again combine the two birds into one record, and classify as a non-eagle. One missed eagle was flying alone and simply not detected by IdentiFlight. IdentiFlight detected 5958 birds during the periods when observers were sampling that were not detected by observers (Fig. 2). Observers therefore spotted 1224 of the 7182 (17%) birds observed by IdentiFlight within 1000 m (Table 1).

Although observers missed almost 6000 of the IdentiFlight birds, those missed birds tended to be relatively farther away and to the west as compared to observed birds (Figs. 2, 3). Logistic regression of whether or not observers detected individual birds detected by IdentiFlight revealed that detection by observers decreased by horizontal distance ($\beta = -0.003$, SE < 0.001), and height ($\beta = -0.005$, SE < 0.001), and increased to the east ($\beta = 0.48$, SE = 0.05, Figs. 2, 3). Detection was not associated with 'northness' ($\beta = -0.003$, SE = 0.025, Fig. 3). See Table A1 for the AIC results. Mean distance to the nearest IdentiFlight unit for a missed bird was 554 m (SD = 223, Fig. 2); the mean distance of a bird that was detected by observers was 383 m (SD = 198, Fig. 3).

Table 1
Numbers of birds detected or not detected by either IdentiFlight or observers. Note that for a bird to be considered 'not detected' it must have been detected by one system, but not the other.

	IdentiFlight	Observers
Detected	7182	1277
Not detected	53	5958

3.2. Identification

Using photos of the 1224 bird flights detected by both observers and IdentiFlight within 1000 m, we were able to classify 1162 as eagle ($n = 149$) or non-eagle ($n = 1013$). The three non-eagle species most often misclassified by IdentiFlight were Turkey Vultures, Red-tailed Hawks, and Common Ravens. We were unable to classify 62 birds because their images were too blurry. IdentiFlight correctly classified all but nine of the eagles (as determined by photographs) as eagles, for a sensitivity of 0.94 (SE = 0.02, Fig. 4, Table 2) and false negative rate (1 – sensitivity) of 0.06. Of the birds determined by photographs to be non-eagles, IdentiFlight classified 287 as eagles for a specificity of 0.72 (SE = 0.01, Fig. 4, Table 2) and false positive rate (1 – specificity) of 0.28. Observers had a higher rate of specificity (0.98, SE < 0.01) than sensitivity (0.69, SE = 0.04). The differences between sensitivity and specificity of IdentiFlight and observers were both statistically significant ($p < 0.01$). Therefore, observers were significantly better at identifying non-eagles, whereas IdentiFlight was significantly better at identifying eagles. Relationships between false positive error rates and distance were not significant for IdentiFlight or observers ($p > 0.05$). There was also no relationship between false negative rates and distance for IdentiFlight (Fig. 4). However, observers were 26% (SE = 7%) more likely to commit false negative errors for every 100 m increase in distance ($p < 0.01$, Fig. 4).

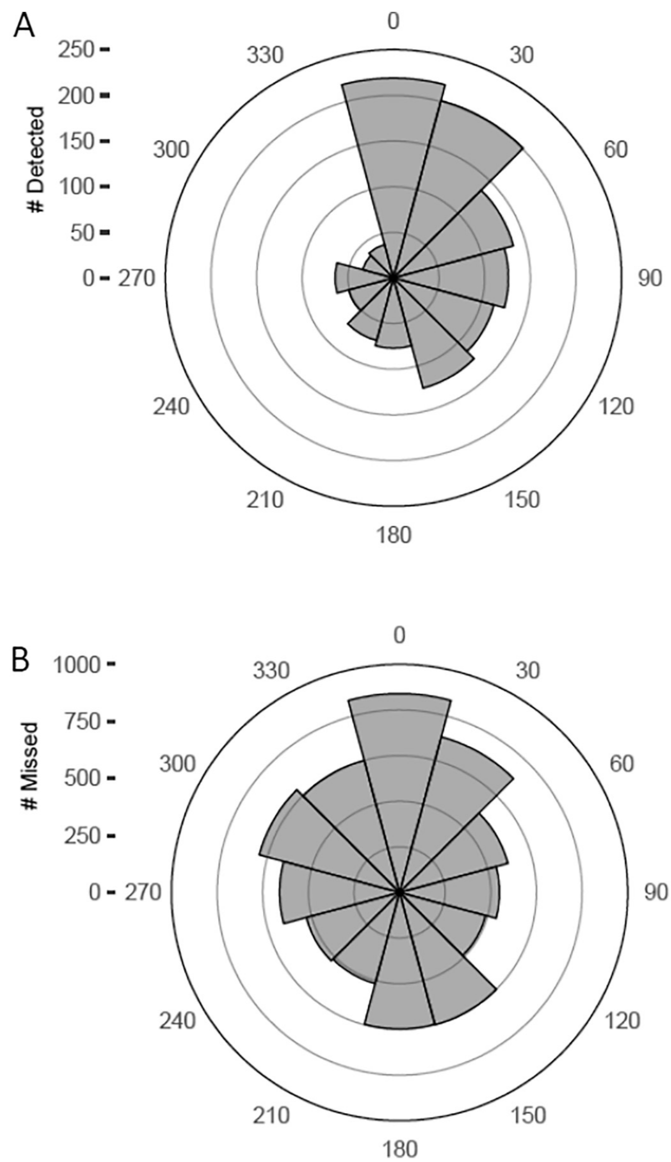

Fig. 3. Wind rose plots indicating the compass direction of birds at classification that were detected ("Detected"; n = 1224) or missed ("Missed"; n = 5958) by observers. All birds presented were detected by the IdentiFlight system.

3.3. Time and distance at classification

The distribution of times until classification for IdentiFlight across all observed bird flights was highly skewed with most birds classified almost instantaneously (Fig. 5). The median time till classification was 0.2 s across all bird flights (2.5 and 97.5 percentiles = 0.0—73.2), 0.4 s (2.5 and 97.5 percentiles = 0.0—129.48) for birds classified as eagles, and 0.2 s (2.5 and 97.5 percentiles = 0.0—34.40) for birds identified as non-eagles (Fig. 5). The median distance from the nearest IdentiFlight tower at which birds were classified as non-eagles was 537 m (2.5 and 97.5 percentiles = 174—1109, Fig. 5). The median distance at classification for birds classified as eagles was 793 m (2.5 and 97.5 percentiles = 269—1191, Fig. 5), meaning that birds classified as eagles were detected and classified at a farther median distance than those classified as non-eagles, although there was substantial overlap in distances. Across all birds, the median distance at which birds were classified was 609 m (2.5 and 97.5 percentiles = 191—1173, Fig. 5).

4. Discussion

The results of this first test of IdentiFlight suggest that it can effectively detect birds as large, or larger than an American Kestrel in flight—detecting 96% of the birds recorded by observers and almost 6000 more than did observers. Further, IdentiFlight classified most of these birds within split-seconds and at median distances well over 500 m. Of the birds detected by both IdentiFlight and observers, IdentiFlight correctly classified > 90% determined from photographs to be eagles and maintained a relatively low false negative rate across distances (Fig. 4). Conversely, IdentiFlight correctly classified roughly 70% of birds determined from photographs to be non-eagles, a pattern contrasting with that of observers.

The ability of observers to detect and identify birds in flight declined strongly with distance. Other studies have demonstrated negative effects of distance on the ability of observers to detect flying raptors (Berthiaume et al., 2009; Nolte et al., 2016). To our knowledge, although some studies have examined detection, no study has examined the ability of observers to identify birds in flight. We likely did not detect a relationship between IdentiFlight's false negative classification rate and distance because there were only nine false negatives. Because IdentiFlight is currently designed to protect eagles from collisions with wind turbines, IdentiFlight is specifically programmed to have a low false negative rate at the cost of sometimes misclassifying a non-eagle. Differences between the detection and classification ability of IdentiFlight and the observers under the sampling scheme we implemented are perhaps partly due to the effect of distance on human detection rates and IdentiFlight's programming. Observers were also more likely to miss birds flying west of the survey area. This 'blind spot' is possibly because most birds were flying north of the study area (Fig. 3) and perhaps that is where observers more often faced during surveys. Conversely, IdentiFlight continuously scans the sky in a 360-degree radius, thereby avoiding a directional blind spot.

It is important to reiterate that our study used observers to obtain an index of the number of birds available to be detected, as other studies have (Alquezar and Machado, 2015; Campos-Cerqueira and Aide, 2016; Dokter et al., 2013; Gerringer et al., 2016; Leach et al., 2016). Our approach therefore does not produce an absolute detection probability, but instead an index of the ability of IdentiFlight to detect known birds. The premise of this and similar studies is that if the automated system detects a sufficient proportion of birds detected by humans, then the automated system is effective.

We designed this study for the specific purpose of beta-testing IdentiFlight—essentially creating a network of observers that mirrored IdentiFlight in temporal and spatial arrangement. We further aggregated the data so that the composite effort of four observers was compared to that of four IdentiFlight towers. Thus, although the observers individually followed the protocol of USFWS (2013), composite data from our observers are not comparable to those collected by point counters, hawkwatchers, or other methods of counting birds in flight. Our results therefore preliminarily suggest that IdentiFlight might perform the tasks currently performed by biomonitors, but do not test the efficacy of the current biomonitoring scheme.

Although our study suggests that automated camera technology is useful in detecting and classifying eagles, further testing is needed to confirm our results and directly examine the efficacy of IdentiFlight and similar systems for applied use in informed curtailment. We designed our method of combining observations between IdentiFlight units that occurred within 1 min and 120 m to be conservative so as not to over count observations made by IdentiFlight. Thus, our results might understate the detection ability of IdentiFlight. The logistics of our study site precluded us from using trained birds or gps-tagged resident eagles for stronger inference into IdentiFlight's capabilities, but future studies should endeavor to employ such methods. Rates of detection and classification might be affected by seasonality, weather, and the composition of the bird community, yet our study occurred at one site over

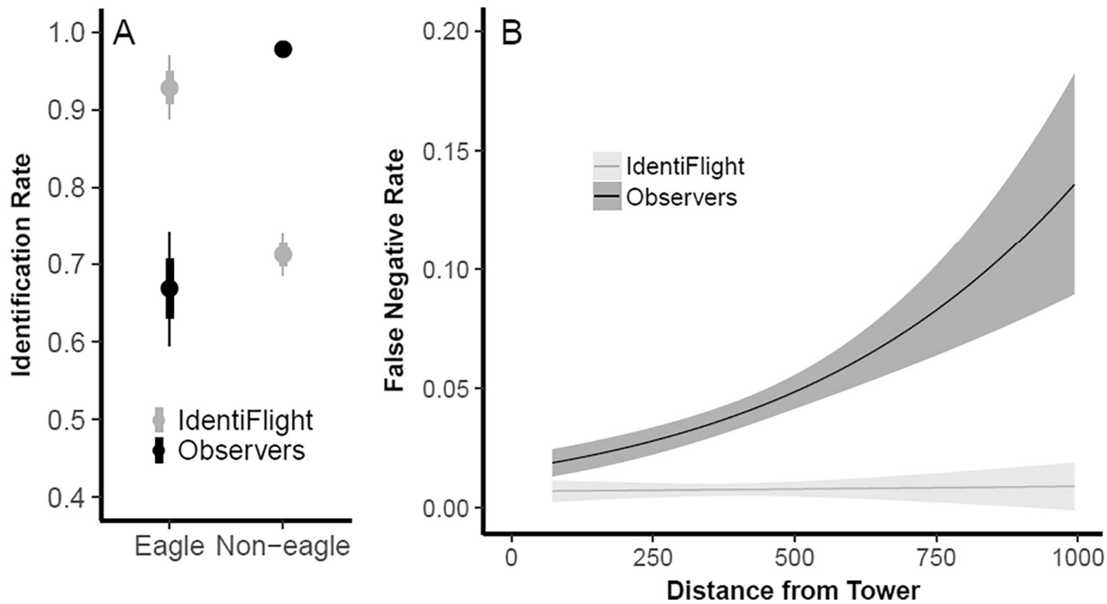

Fig. 4. Rates of correct identification of eagles (sensitivity) and non-eagles (specificity) for the IdentiFlight system and observers determined by reviewing photographs (A). Dots represent the mean, thick lines represent standard errors, and thin lines 95% confidence intervals. B) The relationship between the false negative rate and distance for observers and IdentiFlight. Solid lines represent the mean prediction from a logistic regression model and shaded areas represent ± SE from the mean predictions.

Table 2
Numbers of birds determined to be either eagles or non-eagles by a team of experts (Truth) versus their classifications as eagle or non-eagle by IdentiFlight and observers.

		Truth	
		Eagle	Non-eagle
IdentiFlight Classification	Eagle	140	287
	Non-eagle	9	726
Observer Classification	Eagle	102	21
	Non-eagle	47	992

the course of a single month. More testing of IdentiFlight under a variety of conditions is therefore needed. Further, due to logistical constraints, we only examined photographs of birds that were detected by both observers and IdentiFlight. It is possible that this subset of birds is not representative of the entire set of classifications made by IdentiFlight.

In addition to wind power applications, automated monitoring systems such as IdentiFlight might be useful for other situations such as raptor migration counts, pre-construction surveys at potential energy development sites, and airports. Perhaps the biggest drawback to IdentiFlight, especially relative to observers, is that the IdentiFlight units cannot detect birds below -1°. This limitation is compounded when the IdentiFlight units are placed on peaks or ridgelines, although it can be overcome by overlapping the detection zones of units (see

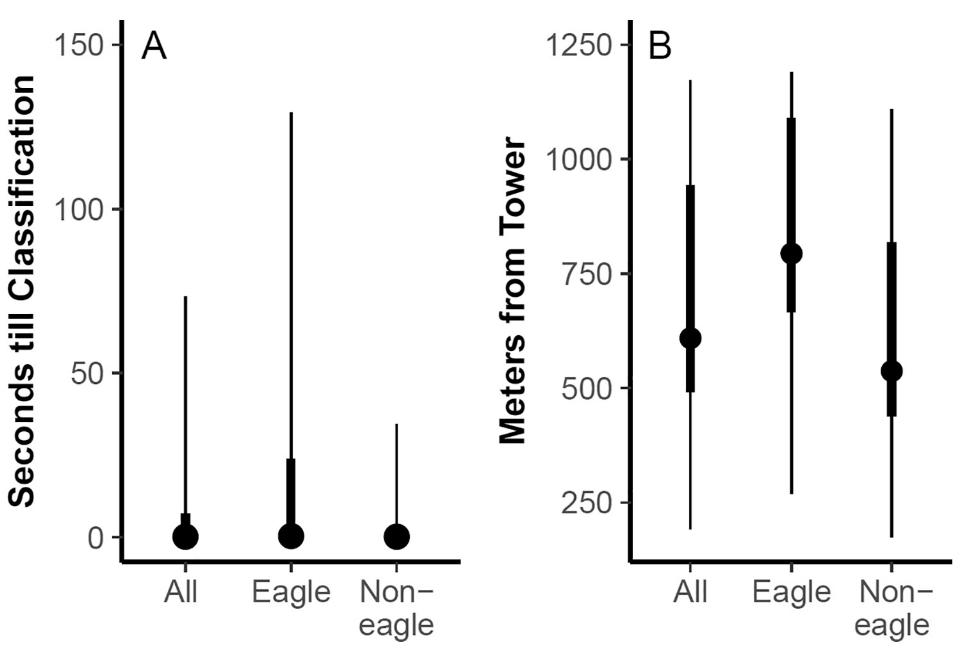

Fig. 5. Times from detection until classification and distances from the nearest IdentiFlight unit at classification for all birds, birds classified as eagles, and birds classified as non-eagles by IdentiFlight. Dots represent median, thick lines represent the 34th and 84th percentiles (representing ± 1 SD under a normal distribution), and thin lines represent the 2.5th and 97.5th percentiles.

online Appendix).

Future technological advancements might further enhance the utility of IdentiFlight. We did not distinguish between Bald and Golden Eagles in this study, mostly because of their equal protection under the Bald and Golden Eagle Protection Act (1940) and similarities in subadult plumage. However, software upgrades under development might allow species-specific identifications and incorporation of flight trajectories into curtailment decisions. The classification algorithm might also be adjusted to have a greater specificity, if users wish to lower the false positive rate. As technology improves, the need to survey wildlife increases, and conservation funding remains scarce, researchers will increasingly rely on automated technology (Arts et al., 2015; August et al., 2015). Automated monitoring systems such as IdentiFlight might therefore become important tools in the effort to monitor and conserve wildlife.

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Appendix A

Table A1
Number of parameters (k) bias-corrected Akaike's Information Criterion value (AIC_c), difference in AIC from the top ranked model (ΔAIC_c), model weight (w_i), and log-likelihood (LL) for logistic regression models of global tracked detected by IdentiFlight that were missed (0) or observed (1) by observers. For Eastness, Distance, Height, and Northness, an "X" represents the presence of that covariate in the model.

Eastness	Distance	Height	Northness	k	AIC_c	ΔAIC_c	w_i	LL
X	X	X		4	5677	0	0.726	−2834.48
X	X	X	X	5	5678.9	1.95	0.274	−2834.45
	X	X		3	5760.4	83.4	0	−2877.18
	X	X	X	4	5762.3	85.33	0	−2877.14
X	X			3	5914	237.03	0	−2954
X	X		X	4	5914.3	237.29	0	−2953.12
	X		X	3	6018.1	341.15	0	−3006.06
	X			2	6018.1	341.16	0	−3007.06
X		X		3	6074.1	397.1	0	−3034.03
X		X	X	4	6075.6	398.61	0	−3033.79
		X		2	6203.7	526.77	0	−3099.87
		X	X	3	6205.6	528.63	0	−3099.79
X			X	3	6390.2	713.22	0	−3192.09
X				2	6394.1	717.1	0	−3195.03
			X	2	6557.4	880.46	0	−3276.71
				1	6560.4	883.45	0	−3279.21

Appendix B. Online appendix

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2018.04.041.

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