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Research Article

Incorporating Detection Probability to Estimate Pheasant Density

LACEY T. WILLIAMSON,[1,2] *Pennsylvania Cooperative Fish and Wildlife Research Unit, The Pennsylvania State University, 419 Forest Resources Building, University Park, PA 16802, USA*

W. DAVID WALTER, *U.S. Geological Survey, Pennsylvania Cooperative Fish and Wildlife Research Unit, The Pennsylvania State University, 403 Forest Resources Building, University Park, PA 16802, USA*

SCOTT R. KLINGER, *Pennsylvania Game Commission, 2001 Elmerton Avenue, Harrisburg, PA 17110, USA*

DUANE R. DIEFENBACH, *U.S. Geological Survey, Pennsylvania Cooperative Fish and Wildlife Research Unit, The Pennsylvania State University, 404 Forest Resources Building, University Park, PA 16802, USA*

ABSTRACT Indices of abundance, such as point counts, commonly are used to monitor trends in bird populations. In some circumstances, however, an index of abundance provides insufficient information for making management decisions and accurate density estimates are necessary. Wild ring-necked pheasants (*Phasianus colchicus*) were translocated to 10 study areas in Pennsylvania from 2007 to 2014 with the goal of establishing female densities of 3.86 pheasants/km^2. We developed a population density estimator that used 3-minute crowing counts adjusted for probability of detection to estimate male pheasant density and flushing surveys to estimate the female:male ratio. To account for detection probability, we estimated the probability a pheasant was available to be detected by monitoring crowing frequency of male pheasants fitted with radio-transmitters and the probability an observer was able to detect a crowing pheasant at distances from 0 to 0.93 km. We found the probability a pheasant crowed during 3 minutes decreased linearly over our survey period from 0.66 in mid-April to 0.46 by the end of May. At the farthest distance we were able to accurately detect a crowing pheasant. We estimated the probability of detecting a pheasant at 0.80 km to be 0.019 ± 0.005 (SE), which means that we could not assume any fixed distance beyond which crowing birds could not be detected. Therefore, we replaced the probability of detection in the standard distance sampling estimator with the effective area of detection. The estimation of the effective area of detection is robust to choice of radius of the point and did not require observers to estimate the distance to crowing pheasants. We estimated the female:male ratio to be 1.02:1, despite the ratio of released pheasants being 4.46:1. Only 1 study area achieved the female density goal ($\hat{D} = 4.16$); the maximum density at all other study areas was <2 females/km^2. The estimator we developed incorporated multiple detection probabilities to provide density estimates and simplified the crowing count protocol by eliminating the need for observers to estimate their distance from a detected bird, which makes the estimator useful for estimation of population abundance when explicit population density objectives must be evaluated.

KEY WORDS density estimation, detection probability, Pennsylvania, *Phasianus colchicus*, restoration, ring-necked pheasant.

Ring-necked pheasants (*Phasianus colchicus*) have been monitored by roadside point counts, minute-long point counts, scat counts, and even using detonations to prompt male pheasants to respond with a crow (McClure 1945). Point counts, such as the Breeding Bird Survey (Nielson et al. 2008), commonly are used as an index of abundance and make the assumption that the individuals detected are a constant, proportional representation of the actual population (Luukkonen et al. 1997, Thompson 2002, Farnsworth et al. 2005). For point counts to provide an index of abundance and be reliable indicators of change over time, the detectability of birds has to remain relatively constant (Johnson 2008) despite potential sources of error including observer ability to detect birds correctly (Carney and Petrides 1957, Rosenstock et al. 2002), seasonal trends (Nelson et al. 1962), differences in the time and duration of maximum calling (Kimball 1949), and variation and effect of environmental factors (Buckland et al. 2001). Without explicitly estimating detection probabilities, it may be unclear whether a change in an index of abundance is due to differing detection probabilities, an actual change in population size, or a combination of detection probability and population (Farnsworth et al. 2005).

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[1]*Present Address: 2014 Martinsburg Pike, Winchester, VA 22603.*
[2]*E-mail: lacey.williamson2@gmail.com*

An index of abundance can be used to monitor population trends over time, but there are instances when density estimates with measures of precision are necessary, such as when assessing success of population restoration efforts (Farnsworth et al. 2005) or comparing populations (Gates 1966). By adjusting point counts for detection probabilities, it is possible to estimate population size and density. The need for accurate density estimates has led to the development of monitoring techniques that account for detection probability of <1.0. Some of the methods developed to estimate detection probability for point counts include distance sampling (Buckland et al. 2001), double observer sampling (Nichols et al. 2000), removal models (Farnsworth et al. 2002), and a combination of these techniques (Farnsworth et al. 2005, Amundson et al. 2014). Issues with detection probability, such as differences among observers in the ability to detect individuals, can increase variance and lead to less precise population estimates (Diefenbach et al. 2003). Multiple factors that influence detection probability likely are important to consider and account for when estimating abundance, such as the probability a bird is available to be detected by an observer and the probability an observer is able to detect a bird given it is available to be detected (Farnsworth et al. 2005, Diefenbach et al. 2007).

The Pennsylvania Game Commission (PGC) created wild pheasant recovery areas (WPRAs) in 2007 and these sites were closed to pheasant hunting and did not receive pen-reared pheasants. Because the survival rate of pen-reared pheasants in the wild is poor (Krauss et al. 1987, Diefenbach et al. 2000), the PGC translocated wild pheasants from Montana and South Dakota, USA. To assess if these pheasant restoration efforts were successful, the PGC needed density estimates rather than an index of abundance typically used to monitor population changes over time. The PGC expected that a minimum population density of 3.86 females/km^2 could be self-sustaining with hunting. Our objective was to develop methods to estimate density of pheasants on WPRAs and use the resulting density estimates to assess whether population density goals were achieved.

STUDY AREA

We monitored wild, translocated pheasant populations at 2–5 study areas in each of 4 WPRAs that had $>40.5\,\mathrm{km}^2$ of potentially suitable breeding and overwintering habitat for pheasants in Pennsylvania from 2013 to 2016 (Table 1, Fig. 1). The topography of WPRAs consisted of ridges and valleys and varied in elevation across all WPRAs from 106 m to 818 m, but elevation range within WPRAs was 325–540 m (U.S. Geological Survey's Center for Earth Resources Observation and Science 2010). The median frost-free growing days on WPRAs ranged from 143 days to 193 days (National Oceanic and Atmospheric Administration [NOAA] 2017*a*) and the average yearly precipitation ranged from 104 cm to 117 cm (NOAA 2017*b*). The study areas are classified as having a humid continental climate with warm, hot summers and cold winters; precipitation is consistent throughout the year. Predators of ring-necked pheasants and pheasant nests found within the study areas included raccoon (*Procyon lotor*), striped skunk (*Mephitis mephitis*), coyote (*Canis latrans*), red fox (*Vulpes vulpes*), gray fox (*Urocyon cinereoargenteus*), Virginia opossum (*Dedelphis virginiana*), great-horned owl (*Bubo virginianus*), and red-tailed hawk (*Buteo jamaicensis*).

The majority of the landscape in the Somerset WPRA was used for agriculture (61.5%) and other major land cover types were forest (14.1%) and developed (10.7%; U.S. Department of Agriculture National Agricultural Statistics Service Cropland Data Layer 2015). The Central Susquehanna WPRA had a similar landscape composition with 54.4% agriculture, 16.0% forested, and 10.6% developed. The Hegins-Gratz WPRA had a large proportion of the area in agriculture (63.8%) and forest (19.6%) with only 8.8% developed. The Franklin WPRA was 63.5% agriculture, 13.5% forest, and 12.8% developed. The majority of the land within WPRAs was privately owned, and the primary agricultural crop was corn, except 1 WPRA (Somerset) where hay was the most common crop.

METHODS

We trapped wild pheasants in South Dakota (2007, 2010, 2011, and 2014) and Montana (2007–2009) from January to March and translocated them to WPRAs. We used standard wire funnel traps ($1\,\mathrm{m}^2$) and bait (Leopold et al. 1938). We checked the traps daily and held pheasants in pens until 100–300 birds were available for shipment. Before transporting pheasants, we tested all birds for avian influenza and parasites. We placed 4–9 pheasants in each crate for transportation. All birds received a leg band and some pheasants received necklace-style radio-transmitters (11 g; Lotek Engineering, Ontario, Canada) upon release. As control sites, we did not release pheasants in 2 study areas (Washingtonville South and North Franklin) at 2 different WPRAs to test if pheasants would naturally establish a population if habitat was available. All procedures for trapping and handling pheasants were part of a study plan approved by the Pennsylvania Game Commission using protocols recommended by the American Ornithologists' Union.

We conducted crowing count surveys at the nearest location on a road to randomly placed points across each study area. Unlike traditional crowing count surveys, we did not conduct surveys as a transect of points but as independent survey points such that the sampling unit was the point, not the transect (Buckland et al. 2001). Observers conducted crowing counts between 16 April and 31 May, 2013–2016. We conducted surveys beginning 30 minutes prior to sunrise and completed them no later than 0900 hours in acceptable weather and noise conditions (i.e., low wind speed, temperature $>0°\mathrm{C}$, and no persistent precipitation). Observers conducted surveys for 3 minutes and recorded the number of individual male pheasants that crowed during the survey period. Observers did not attempt to record distance to the crowing pheasant. We visited each survey point 1–12 times during the breeding period.

Table 1. Number of survey points at which we conducted crowing counts and size of the wild pheasant recovery areas (WPRAs), Pennsylvania, USA, 2013–2016.

	Number of survey points				
WPRA study area	**2013**	**2014**	**2015**	**2016**	**Area (km^2)**
Central Susquehanna	128	133	133	213	511.6
Greenwood Valley	20	20	20	29	66.0
Pennsylvania Power and Light	24	24	24	48	80.9
Turbotville North	30	30	30	40	78.9
Washingtonville South	24	29	29	41	90.9
Washingtonville West	30	30	30	55	80.2
Hegins-Gratz	60	60	60	80	255.8
Hegins	20	20	20	30	62.2
North Gratz	20	20	20	25	40.5
South Gratz	20	20	20	25	42.1
Somerset	31	31	31	35	69.2
North Somerset	20	20	20	23	51.3
South Somerset	11	11	11	12	17.8
Franklin	34	34	34	45	339.9
North Franklin	15	15	15	15	35.8
South Franklin	19	19	19	30	55.7

To increase precision of pheasant density estimates, crowing counts can be adjusted for 2 factors related to the probability of detecting a pheasant (Farnsworth et al. 2005, Diefenbach et al. 2007): the probability a pheasant crowed during the 3-minute interval and the probability a crowing pheasant was heard by an observer. To estimate male pheasant density, we began with the modified distance sampling estimator (Diefenbach et al. 2007):

$$\hat{D}_{males} = \frac{m}{\hat{p}_A \times \hat{p}_{D|A} \times \pi r^2 \times t},$$

where $\hat{D}$ is the estimated density; m is the number of detected males crowing; $\hat{p}_A$ is the estimated probability that a male pheasant will crow during the survey period; $\hat{p}_{D|A}$ is the estimated conditional probability that the observer detected the crowing male pheasant given that it is available to be detected; πr^2 was the area surveyed; and t was the number of surveys completed. We used the estimated male pheasant density and the estimated population sex ratio from flushing surveys to estimate female density.

To estimate p_A, we observed male pheasants on 2 WPRAs (Franklin and Central Susquehanna) located via radio-transmitters during the breeding season (20 Apr–31 May) in 2014 and 2015 for a 30-minute time interval between a half hour before sunrise to 0830 hours. Over the course of the study, 6 different observers recorded the number of times a bird crowed within a 3-minute survey, yielding 10 3-minute surveys for each observation session per pheasant. We monitored each male pheasant $\geq$3 times throughout the breeding season under conditions matching the crowing count protocol. We classified a bird as available to be detected if it crowed $\geq$1 time within a 3-minute period. We used a generalized linear mixed-effects model and specified a binomial distribution (Bates et al. 2015) to estimate p_A. To estimate how p_A changed over time, we created models including a linear effect of calendar day, a linear and quadratic effect of calendar day, and an intercept-only model. We treated the individual bird as a random effect to account for heterogeneity in crowing frequencies among individuals. We stratified the surveys into 3 periods (21 Apr–1 May, 2–12 May, 13–31 May). We estimated p_A for the midpoint of each period and used this in the density estimator (Equation 1). Because of the large variation in the number of surveys completed per point, we adjusted the number of birds heard by the number of visits for each period.

To estimate $p_{D|A}$, we monitored the ability of observers to detect crows of 21 male pheasants at distances of 0.03–0.93 km on 2 WPRAs (Somerset and Central Susquehanna). During the 2010–2013 breeding season, 2 observers located a male pheasant via its radio-transmitter and waited for a 2-minute adjustment period. Subsequently, both observers recorded the number of times they heard the pheasant crow for 10 minutes. The first observer remained near the pheasant while the second observer moved away from the bird at 0.18-km intervals and the listening periods were repeated. By documenting which crows the second observer missed, we were able to estimate $p_{D|A}$ as a function of distance from the observer. We estimated $p_{D|A}$ using logistic regression with the logistic function scaled by the probability of detection at distance 0 so that $\hat{p}_{D|A} = 1.0$ at distance 0. We used the logistic detection function to estimate the effective area of detection (Buckland et al. 2001). Effective area (EFFAREA) is the area in which the estimated proportion of detections beyond a specified distance is equal to the estimated proportion of missed detections within that distance (Buckland et al. 2001). By using the effective area, we avoided arbitrarily defining a detection radius for the crowing counts, which resolved the problem of not measuring the distance of a crowing pheasant from the observer during the count surveys. Therefore, we modified the male density estimator:

$$\text{EFFAREA} = \hat{p}_{D|A} \times \pi r^2 \quad \hat{D}_{males} = \frac{m}{\hat{p}_A \times EFFAREA \times t}.$$

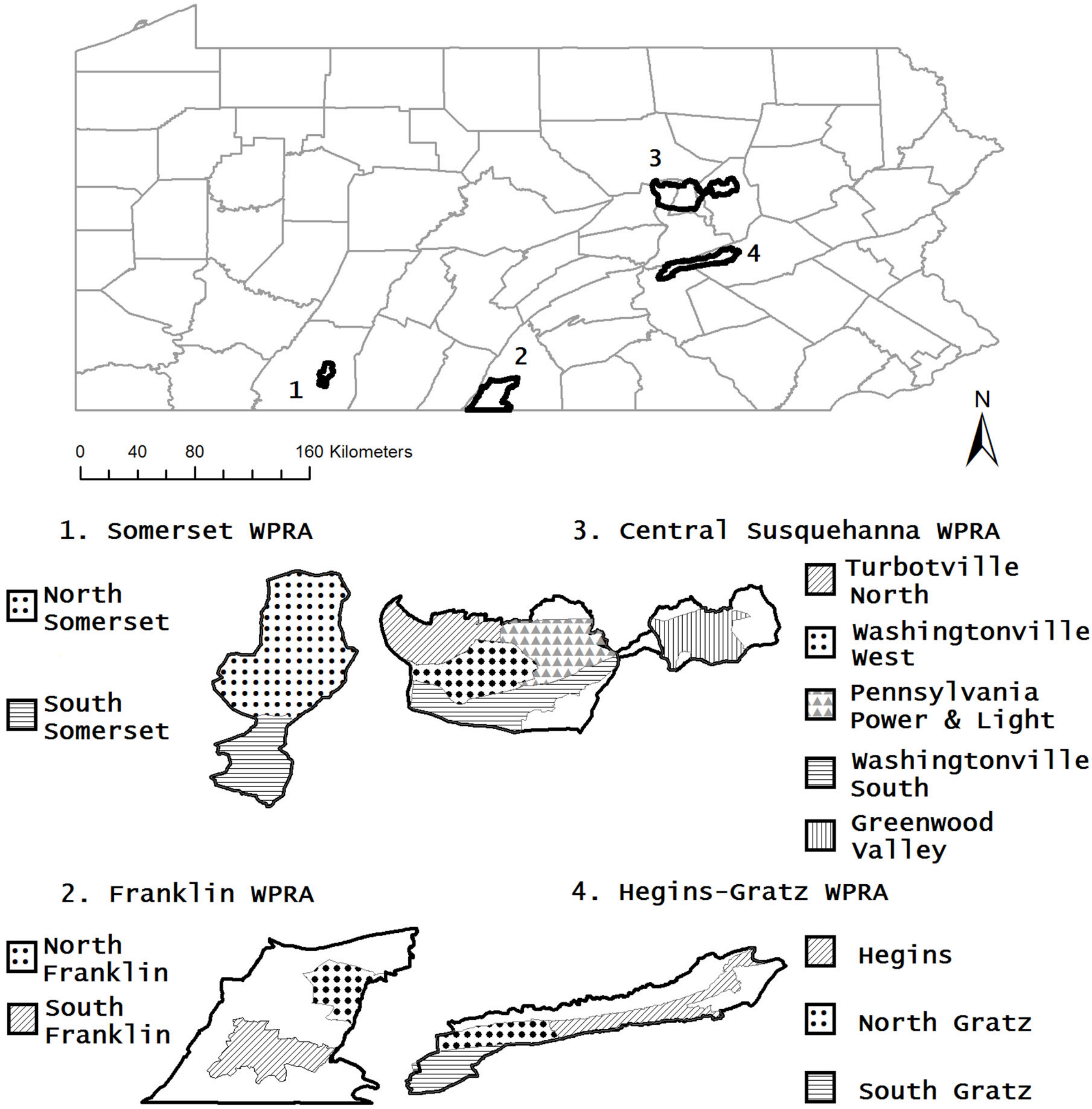

Figure 1. The locations of wild pheasant recovery areas (WPRAs) and county outlines in Pennsylvania, USA, 2013–2016.

We estimated the number of males ($\hat{M}_v$) and variation $\left(\hat{\text{var}}\left(\hat{M}_v\right)\right)$ for each period separately because of variation in crowing frequency based on calendar day. By including t_v, the number of visits in survey period v, in the density estimation, we accounted for an unequal number of surveys per survey point.

$$\hat{M}_v = \frac{m_v}{\hat{p}_{Av} \times t_v} \quad \hat{\text{var}}\left(\hat{M}_v\right) = \hat{M}_v^2 \times (cv(m_v))^2 + \left(cv\left(\hat{p}_{Av}\right)\right)^2, \tag{1}$$

where m_v is the number of male birds heard in period v, t_v is the number of surveys across all points in a study area during period v, and $\hat{p}_{Av}$ is the estimated probability a male pheasant crows in period v.

We averaged the 3 male estimates by period ($\hat{M}_v$) to obtain an average male count ($\hat{M}$) and summed the variances $\left(\hat{\text{var}}\left(\hat{M}_v\right)\right)$. We incorporated EFFAREA to estimate overall male density:

$$\hat{D}_{males} = \frac{\hat{M}}{EFFAREA} \quad \text{and}$$

$$\hat{\text{var}}\left(\hat{D}_{males}\right) = \hat{D}_{males}^2 \times \left\{\left(cv\left(\hat{M}\right)\right)^2 + (cv(EFFAREA))^2\right\}.$$

We conducted flushing surveys in winter months (Jan and Feb) from 2013 to 2016 on all of the WPRAs to estimate sex ratio. Observers completed flushing surveys prior to the release of translocated wild pheasants in a given year. We used radio-telemetry, roadside inspections, and input from landowners to identify areas known to have wild pheasants in which we could conduct flushing surveys. Teams of 5–10 people and 4–8 dogs flushed pheasants and surveyed all cover within their defined search area and recorded the sex of pheasants as they were flushed. Observers noted where flushed birds landed to ensure they did not double count birds. We assumed that male and female pheasants had an equal probability of being flushed.

We used generalized linear regression with a binomial link function to estimate the probability of flushing a female pheasant (Bates et al. 2015). To investigate if the probability of flushing a female was influenced by year and to account for heterogeneity among WPRAs, we considered 3 candidate models including an intercept model with year as a random effect, an intercept model including WPRA as a random effect, and an intercept model with year and WPRA as random effects. We estimated the female:male ratio as the logit of the estimated probability of flushing a female obtained from the best model.

To estimate female density, we multiplied the estimated male density by the sex ratio (the odds ratio of the probability of flushing a female pheasant):

$$\hat{D}_{females} = \hat{D}_{males} \times \frac{\hat{P}(female)}{1 - \hat{P}(female)}.$$

We used the delta method to estimate standard error for female pheasant density (Williams et al. 2002). We fit models using maximum likelihood when estimating the probability of a pheasant being available to be detected and used restricted maximum likelihood when fitting models for estimating the probability of flushing a female pheasant. We analyzed all data in Program R using package lme4 (Bates et al. 2015, R Core Team 2015) and selected the best model according to Akaike's Information Criterion adjusted for sample size with the lowest score (AIC_c; Burnham and Anderson 2002) using restricted maximum likelihood estimation (Zuur et al. 2009).

RESULTS

We released 2,328 pheasants and 1,902 of those pheasants were female (Table 2). The density of released females ranged from 0.85 pheasants/km^2 to 15.12 female pheasants/km^2 at the study areas. We monitored crowing rates of 21 male pheasants with radio-transmitters (14 pheasants from the Central Susquehanna WPRA and 7 pheasants from Franklin WPRA) to estimate p_A. The best model included an intercept ($\hat{\beta} = 0.29 \pm 0.137$ [SE]) and the calendar day covariate ($\hat{\beta} = -0.23 \pm 0.072$) and indicated that crowing frequency declined linearly over time (21 Apr–23 May; Table 3; Fig. 2). Consequently, we stratified our crowing surveys into 3 periods and estimated the probability a pheasant crowed ($\hat{p}_A$) for the median date of surveys for each period (calendar day 115, 127, and 139). The estimated probability a pheasant crowed during a 3-minute survey period was 0.64 ± 0.037 for period 1, 0.56 ± 0.034 for period 2, and 0.49 ± 0.043 for period 3.

We pooled observer detection data across WPRAs and years (2010–2013). We estimated the effective area to be $0.60 \pm 0.026\,m^2$ and the effective detection radius to be 0.44 km. At the effective detection radius, we estimated the probability an observer detected a pheasant given that it was available to be detected ($\hat{p}_{D|A} = 0.41 \pm 0.005$). The probability of detecting a crowing pheasant decreased as an observer increased distance from the bird. Between 2013–2016, we conducted 155 flushing surveys (89 surveys at Hegins-Gratz WPRA, 49 surveys at Central Susquehanna WPRA, 12 surveys at Franklin WPRA, and 5 surveys at Somerset WPRA) and 1,160 sex identification events occurred. The best model for female:male ratio included the intercept and year as a random effect (Table 4). We estimated the probability of a flushed bird being female to be 0.505 ± 0.024 and a sex ratio of 1.02 ± 0.098 female pheasants for every male pheasant.

The female pheasant density increased on the North Gratz study area (Fig. 3; Table S1, available in Supporting Information online) from 2013 ($\hat{D} = 0.19$) to 2016 ($\hat{D} = 0.93$) but failed to achieve the density goal. The North Somerset study area had a higher density estimate in

Table 2. Year of initial reintroduction, cumulative number of translocated female ring-necked pheasants, and resulting densities (female pheasants/km^2) of released pheasants on wild pheasant recovery areas (WPRAs) and study areas within each WPRA, Pennsylvania, USA, 2007–2014. We did not release pheasants at the Washingtonville South or North Franklin study areas. Densities represent the number of released female pheasants over a study area and are not adjusted for detection probabilities.

				2010		2014	
WPRA study area	**Year of first release**	**Number released in the first year**	**Density**	**Cumulative number released**	**Density**	**Cumulative number released**	**Density**
Central Susquehanna	2007						
Greenwood Valley	2007	52	0.79	115	1.74	115	1.74
Pennsylvania Power and Light	2007	57	0.70	303	3.75	303	3.75
Turbotville North	2007	68	0.86	144	1.83	144	1.83
Washingtonville West	2007	72	0.90	171	2.13	171	2.13
Hegins-Gratz	2011						
Hegins	2011	152	2.44			152	2.44
North Gratz	2011	60	1.48			60	1.48
South Gratz	2011	64	1.52			64	1.52
Somerset	2009						
North Somerset	2009	216	4.21	499	9.72	776	15.12
South Somerset	2009	59	0.85	59	0.85	59	0.85
Franklin	2014						
South Franklin	2014	58	1.04			58	1.04

Table 3. Model selection for linear mixed effects models (each individual bird was treated as a random effect) estimating the probability that a male ring-necked pheasant will crow ≥1 time during a 3-minute period ($\hat{p}_A$), Pennsylvania, USA, 2014–2015.

Model	K[a]	ΔAIC_c[b]	$-2 \times$ log-likelihood	w_i[c]
Calendar day	3	0.0	1,239.6	0.57
Calendar day + (calendar day)^2	4	0.6	1,238.2	0.43
Intercept only	2	8.5	1,250.2	0.01

[a] Number of parameters.
[b] Difference in corrected Akaike's Information Criterion (AIC_c) value from the model with the lowest AIC_c value.
[c] AIC_c weight.

2013 ($\hat{D} = 1.03$) than in 2016 ($\hat{D} = 0.31$). South Somerset also had higher density estimates in 2013 ($\hat{D} = 1.06$) than 2016 ($\hat{D} = 0.35$). The North Franklin study area, where no pheasants were introduced, never had pheasants detected during crowing surveys (Table S2, available in Supporting Information online). The South Franklin study area did not have density estimates for 2013 but did have an increasing density from 2014 ($\hat{D} = 0.16$) to 2016 ($\hat{D} = 0.64$). Only 1 study area, Washingtonville West, achieved and exceeded the female density goal of 3.86 pheasants/km^2 where the highest female density occurred in 2015 ($\hat{D} = 4.16$) but had a lower density ($\hat{D} = 2.85$) in 2016.

DISCUSSION

Point counts may be a cost-effective and simple index to assess bird population trends but are insufficient to assess success of population restoration efforts where a population density estimate is required. Our method of density estimation incorporated 2 separate detection probabilities that influenced the number of birds detected during point counts. Moreover, we used a simplified crowing count protocol and only required observers to count the number of individuals heard crowing without estimating distance.

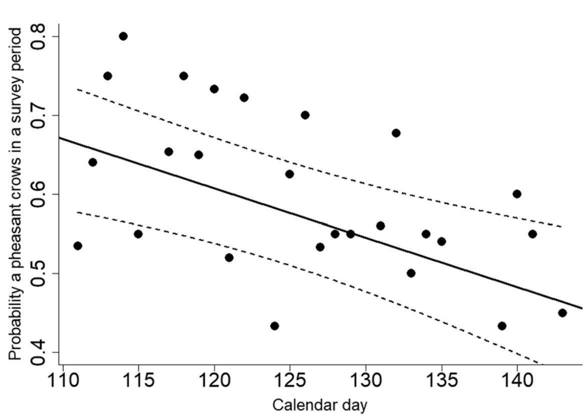

Figure 2. Probability that a ring-necked pheasant equipped with a radio-transmitter ($n = 21$) crowed during a 3-minute survey period based on calendar day plotted with the line of best fit (solid) and 95% confidence intervals (dashed), Pennsylvania, USA, 2014–2015.

Gates (1966) reported crowing frequency to plateau from 25 April to 15 May and we expected to capture the peak of crowing by conducting our crowing counts during this time. We anticipated a quadratic relationship to explain crowing frequency, but our results indicated that we initiated crowing count surveys at or after peak crowing activity by pheasants in our study areas because crowing frequency decreased linearly over time. Without accounting for $p_A < 1.0$ and the decline in crowing frequency over time, density estimates would have been confounded by the date the survey was conducted and the estimator would have been negatively biased. Farnsworth et al. (2005) presented a model that accounted for the probability of a bird being available for detection during a survey, but an assumption of the model was that the probability of a bird vocalizing was constant throughout the survey period. However, our study did not find a constant crowing frequency and our model allowed for a changing probability that a bird is available to be detected. Alternatively, crowing count surveys used as an index of abundance to monitor population trends could be designed to revisit sampling points during the same 1-week or 2-week period each year to ensure relatively constant $\hat{p}_A$ over time.

Many methods of conducting point counts for density estimation that incorporate detection probability ($p_{D|A}$) require 2 observers at all point counts (Nichols et al. 2000, Koneff et al. 2008), observers to measure the distance from the bird when detected (Buckland et al. 2001, Rosenstock et al. 2002), or observers to record the time interval they first detected a bird (Farnsworth et al. 2002). As expected, the farther an observer was from a crowing pheasant, the lower the probability of detecting the pheasant. At the farthest distance we were able to detect a crowing pheasant (0.80 km) our estimated detection function indicated that detection probability was small but >0, indicating that we could not assume that we only heard birds within 0.80 km or a distance at which we could no longer detect crowing pheasants. Rather than directly incorporating the probability an observer detected a male pheasant given that it was available to be detected ($\hat{p}_{D|A}$) at an arbitrarily selected distance in our estimator, we used the estimated effective area of detection. Using the effective area of detection makes the density estimator robust to the choice of point-transect half-width distances when modeling detection probability (Thomas et al. 2002) and eliminated the need to estimate distance when counting crowing pheasants. Because of the difficulty of estimating distance to a crowing pheasant, protocols that relied upon observers to accurately estimate the distance to each crowing bird would violate a key assumption of distance sampling (Buckland et al. 2001).

Although we were able to estimate detection probability based on distance from the bird, we were unable to account for detection differences among individual observers. Detection differences among observers may result from hearing abilities, sensitivity to specific species' songs, or species favoritism (Farnsworth et al. 2002) and can reduce

Table 4. Model selection for the logistic regression models estimating probability that a flushed ring-necked pheasant was male. Variables in parentheses were included as random effects, Pennsylvania, USA, 2013–2016.

Model variables	K[a]	ΔAIC_c[b]	$-2 \times$ log-likelihood	w_i[c]
Intercept + (year)	2	0.0	119.8	0.56
Intercept + (WPRA[d]) + (year)	3	1.5	118.6	0.26
Intercept + (WPRA[d])	2	2.3	122.2	0.18

[a] Number of parameters.
[b] Difference in corrected Akaike's Information Criterion (AIC_c) value from the model with the lowest AIC_c value.
[c] AIC_c weight.
[d] Wild Pheasant Recovery Area.

the precision of the density estimates (Diefenbach et al. 2003). Koneff et al. (2008) reported that detection models including observer effects were favored but encountered issues obtaining estimates of observer detection rates because of small sample sizes. Our estimation of $p_{D|A}$ involved many observers over multiple years, but not all of the observers who conducted crowing counts were involved with estimating $p_{D|A}$. Therefore, we were not able to incorporate observer-specific detection probabilities into the estimator, although it is likely that there are detection differences for individual crowing count observers. Observer-specific estimates of $p_{D|A}$, however, could be readily incorporated into the estimator.

Gates and Hale (1974) reported that the sex ratio during the breeding season could be accurately estimated from a winter (Dec–Mar) field count, as we did with our flushing surveys. We found the sex ratio to be nearly 1:1 despite the sex ratio of released translocated birds being 4.46:1 female to male pheasants. The change in sex ratio likely is the result of differential survival between sexes throughout the year and the fact that our wild pheasant populations were not hunted. Gates and Hale (1974) reported female survival to be correlated with winter weather conditions, whereas winter weather did not greatly influence male survival. Other populations without hunting pressure reported similar sex ratios to our results (Allen 1938, Shick 1947). Therefore, despite a greater proportion of females released on the study areas, differential survival and no hunting pressure could explain the sex ratio becoming equal over a short period of time.

We estimated p_A and $p_{D|A}$ using the wild, translocated birds that were part of the released population. Because p_A can vary by timing of crowing counts and $p_{D|A}$ could vary among observers, detection probabilities will likely differ for other monitoring programs, study areas, or populations and should be estimated for each study. Prior to use in other studies,

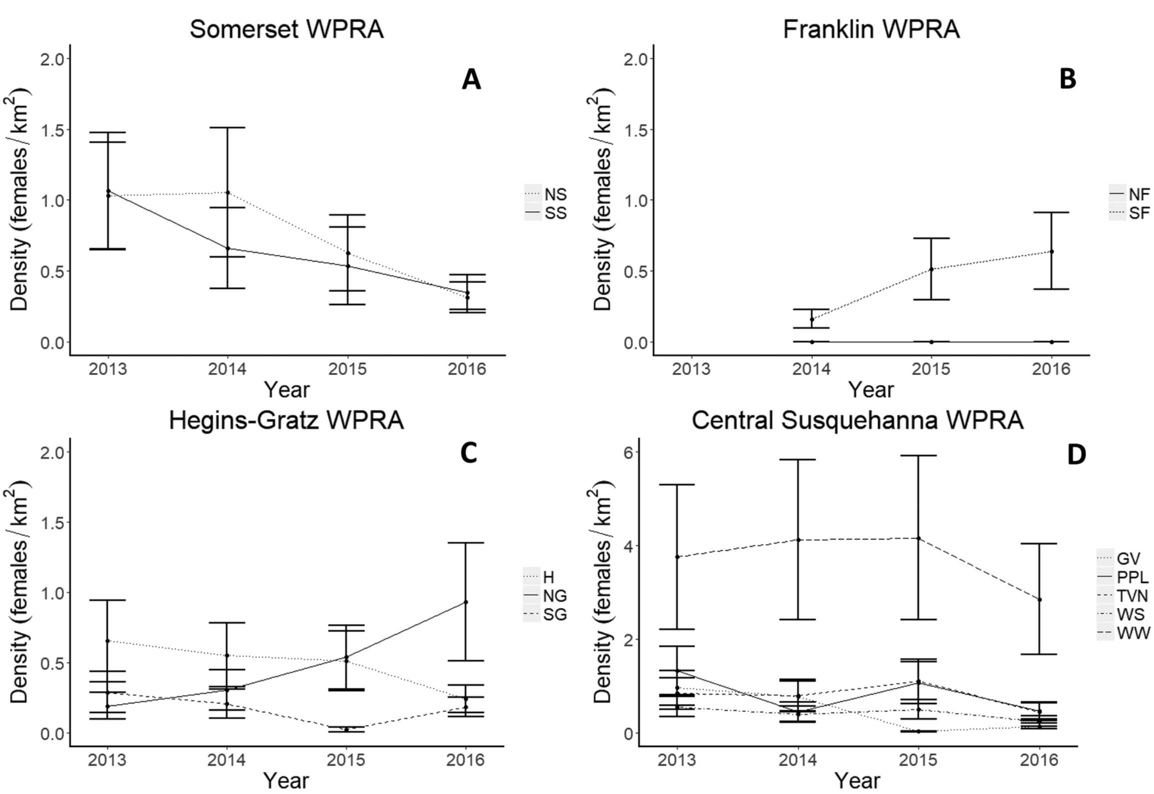

Figure 3. Density estimates (female pheasants/km^2) and 95% confidence intervals for female ring-necked pheasants on the wild pheasant recovery areas (WPRA), Pennsylvania, USA, 2013–2016. The Somerset WPRA (A) contains the North Somerset (NS) and South Somerset (SS) study areas. We did not survey the Franklin WPRA (B) in 2013; it contains the North Franklin (NF) and South Franklin (SF) study areas. We did not detect birds at the South Franklin study area. The Hegins-Gratz WPRA (C) contains the Hegins (H), North Gratz (NG), and South Gratz (SG) study areas. The Central Susquehanna WPRA (D) has a different y-axis because of higher estimated densities and it contains the Greenwood Valley (GV), Pennsylvania Power and Light (PPL), Turbotville North (TVN), Washingtonville South (WS), and Washingtonville West (WW) study areas.

further evaluation of p_A and $p_{D|A}$ are necessary. Adjusting point counts by detection probabilities will not provide perfect estimates, but incorporating detection probabilities can reduce variability (Johnson 2008).

Only 1 of our study areas reached the female pheasant density goal of 3.86 females/km^2 and appeared to achieve a self-sustaining pheasant population. All other study areas failed to reach female densities >2 females/km^2. The WPRAs represented some of the best available pheasant habitat in Pennsylvania, but most study areas (11 of 12) seemed to have inadequate recruitment despite no hunting. It does seem possible to attain self-sustaining pheasant populations in parts of Pennsylvania, but these areas may be limited in size and occurrence.

MANAGEMENT IMPLICATIONS

The estimator we developed could be used in instances where an index of abundance is inadequate for assessing a population, such as reintroduction and restoration efforts. By separately estimating the detection probabilities using birds located with radio-transmitters, we simplified data collection methods for a species in which distance to a crowing pheasant cannot be estimated reliably. Our density estimator did not include variation in detection probabilities among observers, but simple modifications of this estimator could account for this detection probability.

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