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The Effectiveness of an Unmanned Aerial Vehicle in Controlled Fecal Pellet Surveys

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***Abstract*.—The declining costs and increasing capabilities of unmanned aerial vehicles (UAVs) have led to their expanded use in natural resources research and management. Generally, UAV-based data collection involves larger (i.e., more visible) components (e.g., large mammals, blocks of forest) that are more easily observed by UAV cameras. Little research has focused on UAV effectiveness in researching and monitoring relatively small and less visible objects. Fecal surveys are broadly applied methods for determining wildlife occupancy, population abundance and trends, and land use. Potentially, UAVs could improve, or augment, fecal surveys by reducing time and effort expenditures, expense, and impacts on focal species behavior. Yet, their effectiveness and ability to produce accurate and precise estimates have not yet been evaluated. We compared UAV surveys at multiple observation altitudes to traditional in-person on-the-ground surveys to test relative UAV effectiveness. We created artificial survey plots with a randomly assigned number of cereal pellets that mimicked the morphology of rabbit pellets. UAVs provided similar data to in-person counts for presence-absence inference. Additionally, raw counts were similar in pattern to in-person observations for pellets across a range of cover classes but were biased low in most circumstances. Heavy cover negatively affected both methods but resulted in higher undercounting with the UAV. The density of vegetation cover impacts pellet detection for both in-person and UAV-based surveys. Our research demonstrates that UAV-based fecal surveys are viable strategies. Further research in different conditions and fecal shapes is required for full implementation.**

Key Words.—drone; fecal surveys; *Sylvilagus palustris hefneri*; unmanned aerial vehicle.

Introduction

Unmanned aerial vehicles (UAVs) are an emerging technology improving data collection capabilities, data accuracy, research efficiency, cost, and human and wildlife safety in natural resources fields (Linchant et al. 2015; Nowak et al. 2019). The technology includes high-definition camera options, technological integration (e.g., Global Positioning Systems), improving battery life and battery replacement options, modularity and customization, software interface and command capability, commercial availability, and maturing legislation for UAV operation (Christie et al. 2016; Rosario et al. 2020). The increasing capability and diminishing cost of UAVs has spurred their use in natural resources research and management. Over time UAV applications have expanded to include a variety of subfields including wildlife biology (Lopez and Mulero-Pázmány 2019; Scarpa and Piña 2019). Much of the documented use of UAVs in natural resources fields has focused on large-scale subject matter such as analyzing landscape-level vegetation parameters, conducting large-bodied animal counts, and general wildlife population analyses (e.g., Witczuk et al. 2018; Castellanos-Galindo et al. 2019; Scarpa and Piña 2019). We found a variety of research focused on use of UAVs for surveying small or cryptic objects (e.g., Martin et al. 2012; Weissensteiner et al. 2015; Landeo-Yauri et al. 2022). Of note, Martin et al. (2012) tested the ability of UAVs to detect smaller or hidden test objects (tennis balls) in an approximation of wildlife surveys. In some instances, researchers have found UVA-derived estimates of medium sized animals (e.g., sea birds) to be more accurate compared to traditional enumeration methods (Hodgson et al. 2016, 2018). We did not, however, find literature evaluating the use of UAVs to identify or estimate the numbers of very small objects such as rabbit fecal pellets or in pellet-related wildlife surveys.

The attractiveness of UAVs partially stems from research efficiency and safety. They are often able to access areas faster and more safely than walking, driving, boating, or flying and can have a lower level of auditory and visual intrusion than conventional vehicles (e.g., cars, helicopters; Lisein et al. 2013; Linchant et al. 2014). For instance, Castellanos-Galindo et al. (2019) used UAVs to access remote coastal areas including mangroves and rocky coasts during tropical habitat mapping surveys. Natural resources workers face a variety of job-related dangers (Sasse 2003; Watts et al. 2010). Aerial-wildlife surveys in traditional aircraft is a leading cause of death for biologists (Sasse 2003). UAVs are increasingly capable of replacing humans in dangerous situations (e.g., using UAVs instead of humans in helicopters for surveys). As such, UAVs are a relatively low-cost option to increase human and wildlife safety.

UAV capabilities are a continued subject of exploration despite their demonstrated benefits in a variety of natural resources fields. For example, the ability of UAVs to effectively observe small or obscured objects such as fecal pellets is relatively unknown. Fecal pellet surveys are broadly applied in wildlife conservation and management and often require significant amounts of fieldwork. This is generally expensive, time-consuming, physically difficult, and potentially dangerous due to environmental hazards. Ideally, we would reduce fecal pellet fieldwork without reducing data quantity and quality. The pertinent question is whether UAVs produce similar estimates of pellet presence or abundance to provide useful inferences for management and research. If we find UAVs yield biased or inaccurate estimates, can we predict or identify causes for those errors?

We used Lower Keys Marsh Rabbits (LKMR; *Sylvilagus palustris hefneri*) as a model for testing UAV capabilities of seeing cryptic or small animal sign. Fecal-pellet surveys are an important LKMR data collection strategy (Faulhaber 2003; Schmidt et al. 2010; Dedrickson 2011). LKMR habitat primarily consists of areas with low to heavy herbaceous cover including native salt grasses and forbs with little or no forest canopy. We survey hundreds of pre-selected survey plots throughout the LKMR range as part of ongoing population monitoring efforts. Although UAVs preclude some methods related to in-person surveys (e.g., pellet removal for certain density estimation techniques), LKMR surveys are an excellent candidate for UAV-based surveys if researchers can sufficiently detect fecal pellets in UAV-captured photos. Additionally, UAV-based fecal surveys may have broad application. Fecal surveys are a common survey method for a variety of taxa such as lagomorphs (e.g., Hodges and Mills 2008; Murtze et al. 2014), cervids (e.g., DeCalesta 2013), and mustelids (e.g., Birks et al. 2005). Our primary goal was to evaluate the effectiveness of a UAV in detecting objects similar in size and distribution to LKMR pellets. Our objective was to compare accuracy of on-the-ground surveys with UAV-based aerial surveys in multiple cover types.

Methods

Study site.—We conducted our experiment in College Station, Texas, USA, 15 February 2019. College Station is in southeastern Texas in the Post Oak (*Quercus stellata*) Savannah ecoregion (https://enrta.tamu.edu/restoration/). Much of the rural acreage is a mix of upland and bottomland grasslands, with scattered Post Oak Woodlands located both in the upland and bottomland zones. We did not conduct this experiment in the Lower Florida Keys, Florida (location of LKMR), for several reasons. LKMR habitat co-occurs with significant human presence or in areas with restricted access and airspace. Local authorities are reluctant to approve use of UAVs without evidence that supports research effectiveness. College Station was selected due to proximity to research staff, availability of remote testing sites, and presence of vegetation structure similar to LKMR habitat.

Distribution of responsibility.—We carefully separated study setup and data collection responsibilities among the three primary researchers. Separate individuals performed each task of: (1) plot setup and UAV operation; (2) surveyor 1 / ground surveys; and (3) surveyor 2 / image analyses to avoid any observer contamination across surveys. Both surveyors were highly experienced with fecal pellet surveys in general and LKMR surveys in particular.

UAV and operation specifications.—We used a Phantom 4 UAV (Da-Jiang Innovations [DJI], Shenzhen, China) to conduct plot surveys. Our UAV was equipped with a 12.4-megapixel camera (field of view was 94°, 1/2.3” Complementary Metal Oxide Semiconductor [CMOS] sensor) and was capable of a hover-accuracy range (vertical) of ± 0.1–0.5 m depending on positioning method (dji.com/mobile/phantom-4). We kept camera settings at factory defaults: aperture = auto, white balance = auto, style = standard. We flew the UAV using the DJI Go 4 application in P-mode in free flight altitude hold (UAV will hold position). We conducted all flights in Class G airspace (usually classified as uncontrolled airspace 0–1,200 m above ground level). We cleaned the camera lens between each flight as low altitude flying can mobilize dust that coats the equipment. We flew the UAV when wind speed was < 5 kph to improve stability and reduce battery drain. The UAV operator held a U.S. Federal Aviation Administration (FAA) 107 Remote Pilot Certificate at the time of the study. Additionally, the UAV was registered with the FAA as required under U.S. law with all study flights following FAA and Texas A&M University (TAMU) rules and safety guidelines. We submitted a flight plan, which was approved by the TAMU UAV committee prior to our study.

Experimental design: setup.—We surveyed in areas of mixed herbaceous cover with no woody vegetation. We designated four broad herbaceous vegetation cover classes based on conditions we experienced working in LKMR habitat: (1) absent cover (0% herbaceous cover [bare ground]); (2) low cover (< 20% herbaceous cover); (3) moderate cover (20–50% herbaceous cover); and (4) high cover (> 50% herbaceous cover). We assigned 12 circular 1 m^2 plots per cover class (48 plots total; Fig. 1). The field researcher assigned a plot to its respective cover class. We determined the locations for plots in the field (in Texas) based on previous experience with similar cover classes in LKMR research (in Florida). We fully outlined plots using biodegradable marking chalk and we placed survey flags in the center of plots.

We used Kix cereal pieces (General Mills, Minneapolis, Minnesota, USA) as a substitute for rabbit fecal pellets due to their similar size, shape, weight, and coloration (adult pellets ≥ 6.7 mm; Forys 1995; Fig. 2). We based cereal dispersal amount on individual

Figure 1. Unmanned aerial vehicle photograph taken at 3 m altitude of 1 m^2 plots with pseudo rabbit pellets in low vegetation cover, College Station, Texas, USA, in 2020. (Photographed by Ian Gates).

plots on four categories: (1) Absent (0 pellets); (2) low (1–15 pellets); (3) moderate (16–100 pellets); and (4) high (101–300 pellets). These categories were derived from the distributions of counts from current LMKR data collection efforts (Roel Lopez et al., unpubl. reports) and provide useful population monitoring information such as rough occupancy, population trends, and overall range. Each cover class had all four pellet distributions (four plots per cover class). We determined the exact number of pellets placed into each non-zero plot by random number generation within the limits of the category (e.g., moderate = random number within 16–100 pellets). Pellets were placed in plots by the UAV operator who did not reveal these numbers to the other researchers until all data collection was complete.

Experimental design: UAV operation.—After cereal was placed on plots, we first surveyed with the UAV and then conducted on-the-ground data collection. We chose this order of survey to minimize the impact of vegetation or pellet disturbance from on-the ground surveys. UAV flights began in the morning and continued through the afternoon to ensure direct overhead sunlight to minimize shadows. We flew the UAV above the plots at multiple altitudes (3 m, 4 m, 5 m) and took one photograph at each altitude or three photographs total at each plot. These altitudes corresponded to ground sampling distances of 0.13 cm/pixel (3 m), 0.17 cm/pixel (4 m), and 0.21 cm/pixel (5 m). The UAV remained stationary directly above each plot and took a picture at each assigned altitude.

Experimental design: data collection.—One experienced surveyor counted pellets at all ground plots and another counted pellets in UAV images displayed on a 27” 4K monitor. Counts of pellets using the UAV photographs were done sequentially from the highest altitude to the lowest. Consequently, the final count was not independent of the other counts. We took this approach because we assumed that surveys on actual locations would most likely take numerous photographs or videos once over a plot. Throughout the manuscript, references to what we call altitude should be considered a combined effect from altitude and increased vigilance within the surveys. We do make specific comparisons to only the highest altitude to reduce inference based on multiple observations at different altitudes.

Experimental design: data analysis.—We expected that UAVs could be useful tools for monitoring LKMR at various levels of investigation or need. If they could be used accurately to document presence and absence of pellets, then they could be used within an occupancy approach whereas if they effectively reflected patterns of pellet density they may serve as a correlate to existing population estimates (e.g., Schmidt et al. 2010). Ideally,

Figure 2. Comparison of the appearance of (A) pellets of Lower Keys Marsh Rabbits (*Sylvilagus palustris hefneri*) and (B) pseudo pellets. (Photographed by Andrea Montalvo).

estimates derived from UAVs would recapitulate the true numbers of pellets within plots, but if they produced consistently biased estimates, quantifying those biases could be important. We evaluated the ability of UAV-based estimates to provide similar estimates to in-person surveys for presence-absence data, their relative patterns of abundance, and their precision relative to the true number of pellets on a plot. For each level of analyses, we compared the highest altitude of the drone (5 m) to in-person estimates first and as our primary comparison because these estimates were independent. Nevertheless, we also evaluated the lowest altitude to see how increased evaluation across multiple photos and altitude changed patterns and biases in estimates relative to human efforts.

For each plot we quantified the true absence or presence of any pellets to counts made using UAV and in-person surveys. If there was disagreement between the respective methods and the true presence on plot, we coded it as a 0 where we coded the records as a 1 if the method agreed with the true presence on a plot. We used PROC Logistic (SAS; Cary, North Carolina) to quantify the rates, and odds, that a method was correct. For the in-person data set, we used the cover class as a discrete variable and then modeled this as the explanatory variable to the true presence. We modeled the cover as a discrete variable to evaluate differences among the cover classes. For comparison to the in-person data, we used only the information collected at 5 m altitude and evaluated the 95% Confidence Interval (CI) for differences among cover groups. We also modeled information at 3 m altitude to see if it differed from either the 5 m or in-person methods. We report the odds-ratios values for these comparisons with 95% CIs.

We conducted initial plots of the raw count data using both methods, and all altitudes for UAV data, against the true numbers of pellets deployed. These initial plots indicated a potential non-linear response between count methods as the total number of pellets increased. Therefore, to assess the relationship of counts to the true number for similarity in their general pattern, we used General Linear Models with 2nd and 3rd degree polynomial terms as well as single order term where the true numbers of pellets deployed was used as the explanatory variable. We compared the 2nd and 3rd order models to the single order model using Akaike Information Criteria corrected for small sample size (AICc; Burnham and Anderson 2004) to identify which model best described the data. For comparison between the two methods, we examined the 95% CIs around their respective beta estimates for overlap.

We evaluated the precision of counts by calculating a relative deviance of the observed counts versus the true numbers deployed. Because some plots had no pellets deployed, we calculated deviance as:

$$\text{Relative deviance} = \frac{(\text{observed - true})}{(1 + \text{true})}$$

where the observed were the numbers of pellets counted on an individual plot, and at specific altitudes for the UAV, and the true number was the numbers of pellets actually deployed on a plot. For the purposes of statistical analyses, we took the absolute value of this relative deviance value but included the sign and magnitude of this value when we report mean values. The sign of the value was important to consider as it reflected under-detection (negative values) or over-detection (positive values).

We conducted two analyses using these data. In the first analyses, we directly compared the relative deviance of estimates directly between the two methods. Here we made all comparisons between in-person counts and UAV-based counts at 5 m altitude. We evaluated six distinct models in these analyses with explanatory variables considered as follows: (1) A single term model using the method (UAV vs in-person); (2) A single term model with cover class; (3) A single term model with the numbers of pellets deployed on a plot. We considered pellet count as an explanatory variable based on our earlier analyses which indicated changes in estimates based on the numbers of pellets; (4) An additive model with both cover and methods included as discrete variables; (5) An interactive model with terms for method, cover class, and an interaction between method and cover class; and (6) An interactive model with terms for method and the true numbers of pellets deployed on a plot.

We constructed all models in PROC GENMOD using a Poisson distribution with a log link and type III sums of squares. We evaluated other distributions, but the Poisson fit our data best based on our evaluation of histograms and residual plots. We compared these models using AICc and used parameter estimates from the top model. We report all estimates from these models with 95% CIs. We also examined *P*-values from respective effects to make a secondary evaluation of the effects relative to their descriptive ability on deviation in our counts. We used an alpha of 0.05 for rejecting a null hypothesis of no effect. If we found significant differences from specific main effects, we used Nelson-Hsu comparisons to identify groups that were different from one another.

In a secondary analysis of relative deviation, we examined only the UAV data. Our primary goal was to examine the effects of altitude on percentage deviation. Because we felt cover class could potentially exert additive or interactive effects across levels of altitude, we also tested several models including those terms. We tested four models with the UAV data as such: (1) A single effect model with altitudinal effect across 3 m, 4 m, and 5 m altitudes; (2) A single effect cover class model; (3) An additive model with terms from both altitude and cover class; and (4) An interactive model with terms from altitude, cover class, and interactions between cover class and altitude. We tested these four models as we did with our analyses of methods as described above.

Results

For in-person surveys, across all cover types, 47 of 48 (97%) were categorized properly based presence-absence. Only the highest cover class had one of 12 plots that were mis-categorized for presence-absence. At this single plot, we detected no pellets when five were on the plot. For the UAV method, across all altitudes and cover types, 126 of 144 (88%) were correctly categorized for having pellets present or absent. Of the 18 (across all altitudes) that were improperly classified, two (11%) detected pellets when no pellets were present and (88.9%) failed to detect when they were present (Table 1). For in-person surveys, we detected no differences among cover class (χ^2 = 0.015, df = 3, P = 0.997). For UAV data, we could not reject the null hypothesis of no effect based on cover classes at either the 5 m (χ^2 = 0.208, df = 3, P = 0.976) or 3 m level (χ^2 = 0.010, df = 3, P = 0.997).

Regression analyses on the raw count data indicated modest but significant differences between the in-person vs UAV count relative to their true numbers of pellets on the plot. Both methods showed significant positive relationships to the true number of pellets on plots (Fig. 3). In-person counts were best described with a second-order polynomial regression (AICc = 428.38, χ^2= 46.80, df = 1, P < 0.001, β = 0.927 [0.722–1.12], β^2 = -0.0012 [-0.002, - 0.0004]) formulation as AICc values for this model were > 4 different from the single-order model (AICc = 433.85, χ^2 = 93.86, df = 1, P < 0.001, β = 0.638 [0.0.564–0.710],). A 3rd order model was not well supported by the data (AICc = 338.7). In contrast, UAV-based counts (5 m altitude only) were best described with a 1st order model (AICc = 474.01, χ^2= 44.33, df = 1, P < 0.001, β = 0.484 [0.373–0.595]) model compared to the 2nd (AICc = 476.08, χ^2= 10.24, df = 1, P = 0.001, β = 0.578 [0.0.242–0.913]) and 3rd (AICc = 479.23) order models. This beta-estimate for the 1st order model was significantly lower than the comparable parameter for the in-person counts indicating an on-average negative bias for the UAV-counts relative to in-person methods. A regression using UAV-counts at the 3 m altitude was similar to the one we conducted at 5 m (β = 0.55 [0.34–0.65]). Both in-person and UAV surveys methods under-detected pellets on plots on average. In-person surveys had a mean deviance of -0.18 ± 0.231 (standard deviation) whereas UAV surveys had a mean of -0.24 ± 0.852. Commensurate with these means, in-person surveys were negatively biased on 28 of 48 (58%) of plots whereas UAVs were negatively biased on 30 of 48 (62%). In contrast, both methods reported two plots with higher numbers of pellets than were actually on plots. When we examined only the 3 m altitude for UAVs the mean values were -0.31 ± 0.321 but the same proportion were negatively biased.

Our examination of factors that best explained relative deviation revealed that both the method and cover class were important (Table 2). The best model included an effect from both method and cover class with a ΔAICc value of 3.64 compared to the next best model, which included only a cover term. From this top model the effects from both method (χ^2 = 5.87, df = 1, P = 0.015) and cover class (χ^2 = 18.05, df = 1, P < 0.001) were significant when we considered their P-values. All other models we tested included significant effects from both method and

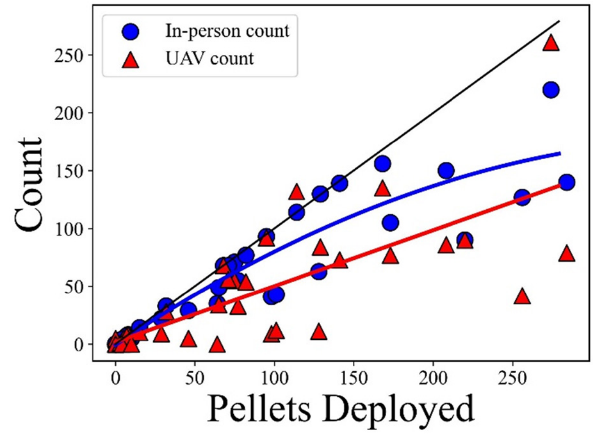

Figure 3. Linear Regression of the counts versus pellets during Unmanned Aerial Vehicles (UAV) test, College Station, Texas, in 2020. The black diagonal line represents the hypothetical ideal relationship between the number of actual pellets and the number of pellets counts. The blue line represents a 2nd order polynomial regression line for in-person counts and the red line a 1st order regression line fit for UAV-based counts.

Table 1. The total number plots (n) and the number and percentage identified correctly for presence-absence status for in-person surveys and Unmanned Aerial Vehicles (UAV) surveys by altitude (meters) at a study site at College Station, Texas.

Type	Cover	n	Correct	Percentage
In-person	Absent	12	12	100%
	Low	12	12	100%
	Medium	12	12	100%
	High	12	11	92%
UAV				
3 m	Absent	12	12	100%
	Low	12	12	100%
	Medium	12	10	83%
	High	12	10	83%
4 m	Absent	12	12	100%
	Low	12	12	100%
	Medium	12	8	66%
	High	12	9	75%
5 m	Absent	12	12	100%
	Low	12	12	100%
	Medium	12	8	66%
	High	12	9	75%

Table 2. Comparison of five competing models hypothesized to explain the percentage deviance of count versus true data for pseudo-pellet surveys conducted using in-person and Unmanned Aerial Vehicles (UAV) methods. Metrics used to compare models follow the form of Burnham and Anderson (2002) where the number of estimable parameters (k), number of observation (n = 96 for all) are used to construct Akaike's Information Criterion corrected for sample size (AICc), the difference between top model and other models (ΔAICc), the model likelihood, and model weight (*w*).

Model	AICc	ΔAIC	k	likelihood	weight
Method + Cover	119.01	0.00	6	1.00	0.83
Cover	122.65	3.64	5	0.16	0.13
Method × Cover	125.13	6.12	16	0.05	0.04
Method × Pellets Deployed	133.15	14.14	6	0.00	0.00
PelletsDeployed	135.51	16.50	2	0.00	0.00
Method	216.69	97.68	3	0.00	0.00

cover class. Across all methods the summed weights indicated cover class to be most influential (cumulative weight = 1.0) where all models with method included as an explanatory variable equaled 0.83. Largely, the results of our analyses indicated that differences in method and cover class were additive rather than interactive (Fig. 4). Mean values of deviance were lowest on average for in-person estimates compared to UAV estimates similarly across all cover classes. Deviations were lowest for both methods when cover was absent (mean = 0.036 ± 0.061), and highest in the moderate (mean = 0.58 ± 0.981) and high cover classes (mean = 0.50 ± 0.357). This pattern is consistent within individual methods although for UAV estimates, the moderate cover class had the highest deviation (mean = 0.92 ± 1.31, z-value = 2.84, $P < 0.010$; Fig. 4). This value was inflated by a single plot where

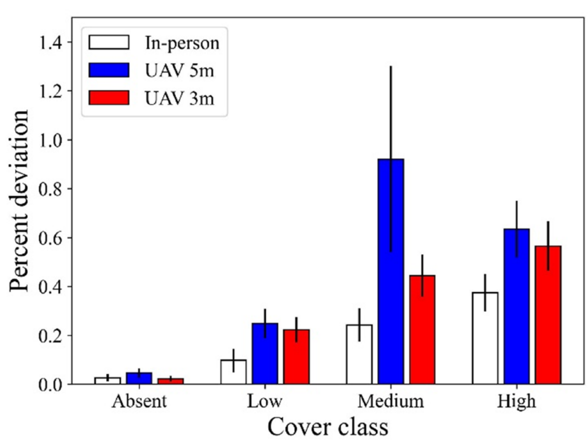

Figure 4. The average percentage deviation ± standard deviation from the true pellet count for in-person surveys and unmanned aerial vehicle surveys conducted at 5 m and 3 m above the observation plot within four vegetation cover class categories (absent = 0% herbaceous cover, low = < 20% herbaceous cover, medium = 20–50% herbaceous cover, and high = > 50% herbaceous cover) for 48 plots surveyed in College Station, Texas, in 2020.

five pellets were counted when none were truly present and yielding a value of five. Had we eliminated this one plot, then the deviation for UAVs in the moderate cover class (mean = 0.54 ± 0.295) would have been lower but similar to mean deviations in the high cover class.

Our analyses of the UAV data indicated no strong effects on deviations from the true value based on altitude but did retain a signal from cover class. Among the models we tested, altitude was not well supported (ΔAICc = 28.6 from top model). Accordingly, no significant effect was detected for altitude in any model we tested ($\chi^2 = 1.41$, df = 2, $P < 0.491$). Although we did not formally examine the data from the 3 m altitude, the patterns of mean values were similar in pattern to our formal analyses across cover class (Fig. 4). The average deviation at the 3 m altitude was lower (mean = 0.33 ± 0.350) than those at the 4 m (mean = 0.39 ± 0.372) or 5 m (mean = 0.40 ± 0.394) altitudes. Cover class was far more powerful in describing deviation in our UAV data (e.g., Fig. 4). Models that included cover and altitude either additively (ΔAICc = 2.9 from top model) or interactively (ΔAICc = 15.8 from top model) seemed not as important as cover class by itself.

Discussion

The use of UAVs in natural resources research and management is widespread and well-documented. This has overwhelmingly tended towards more easily observable phenomena such as basking or foraging animals, vegetation communities, and fire effects (e.g., Biserkov and Lukanov 2017; Witczuk et al. 2018; Castellanos-Galindo et al. 2019; Nowak et al. 2019; Scarpa and Piña 2019). Much of the relevant natural resources work, however, requires observation of small items like fecal pellets.

Our analyses indicate that UAVs and in-person counts of fecal pellets are largely correlated with one another, and to the true numbers of pellets on plots. Both UAVs and in-person surveyors are, on average, biased low in their assessments of the true numbers of pellets on plots. UAVs appear to have a high degree of negative bias and produce more variability in estimates. Both in-person and UAV counts perform well when vegetation cover is absent or low but are less reliable when there is moderate or high vegetation cover. The altitude of the drone heights we used (3–5 m above the ground) were largely uninformative or increased the precisions of counts. We acknowledge that our counts below 5 m were ultimately not independent of one another, but this provides compelling evidence that modest differences in altitude or photographic examination effort did little to improve the precision of the counts. Conceivably had we flown the UAV to a lower altitude (1 m), taken more photographs, or spent more time examining any one of the photographs, our precision would have improved. Nonetheless, our results highlight that even in-person counts are biased low in thick cover. Therefore, we recommend estimating or adjusting the effort for searching when either UAVs or on-the-ground surveyors examine locations with high ground cover. Alternatively, researchers could include an adjustment of pellet counts based on the known biases associated with cover or surveyor skill. For example, our data suggests a modest adjustment of 4% detection rate when vegetation is absent but as much as 63% in vegetation > 75%. We recognize, however, that our results are unlikely to be consistent in all scenarios but in most field settings human-based and drone-based surveys are infrequently going be completely independent. UAVs could work with surveyors on an initial visit to empirically estimate the detection probably on specific plots or in cover classes that are then used on subsequent surveys by the UAV alone.

We found that in-person surveyors were more accurate in their assessments compared to UAVs. Yet, our analyses suggested that when there are large numbers of pellets (> 100), in-person counts became more negatively biased. Human estimates were nearly identical to the true numbers until roughly 100 pellets but appeared to reach an asymptote thereafter. We hypothesize that this resulted from our surveyor not being able to precisely keep track of pellets when they became more numerous. Moreover, the researcher could not revisit counts after having left the plot. Here, drones could ultimately offer an improvement because the photographs are stored for future review by multiple observers or by the potential of using image processing algorithms or even Deep Learning to improve upon counts.

In general, UAVs seem adequate to identify presence and absence of pellets on plots irrespective of cover. Our results did not indicate a significant decline in the ability of UAVs to adequately categorize a plot for presence or absence. Our results highlight the potential limitations of UAVs, but also provide potential approaches for overcoming specific biases. For example, taking photographs (or video) from multiple angles or heights could help improve detection and counts and could conceivably be used within occupancy analytical frameworks to explicitly estimate the probability of detections. In future studies of this nature, we recommend mixing roles so that each researcher is not solely responsible for a single data collection effort (i.e., in-person versus photographs). This would help separate surveyor effects from test effects; however, we note that such observer differences are likely common in most research.

Our research demonstrated several important points. UAVs provided similar, low-biased, numbers to in-person observations for pellets across a range of cover types. Similarly, Goebel et al. (2015) found no significant difference between UAV-based chick counts and ground counts when conducting penguin surveys (Gentoo Penguin, *Pygoscelis papua* and Chinstrap Penguin, *P. antarctica*). Cover type appears to have some capacity to bias UAV results modestly but once the differences in method were accounted for, cover type did not seem to impose an interactive effect where UAVs had additional biases with higher or lower cover. Other studies have found stronger correlations between vegetation cover and detection such as Barr et al. (2018) who found lower colonial waterbird detection by a UAV when vegetation canopy cover was present. More interestingly, there was no important difference in the deviation from the observed to the true numbers based on the survey method. Cover density is likely to reduce the precision and accuracy of pellet counts for both in-person and UAV based surveys, but it is unlikely to alter the relative assessment of the number of pellets among surveyed plots. Both UAV-based surveys and on-the-ground surveys accurately detected categorical pellet abundances (low, moderate, high). For most surveys, UAVs appear to provide sufficient information to determine if pellets are present and their relative abundance. Additionally, altitudes of 3–5 m in height had only modest effects on the raw numbers of pellets detected even though the relative deviance was unaffected. Although focusing on much larger objects, Hodgson et al. (2013) found that UAV altitude did not impact Dugong (*Dugong dugon*) sighting rates or identification capability.

UAVs did relatively well in detecting fecal pellets in a variety of real-world scenarios. As experienced rabbit biologists, we would feel comfortable using UAVs to conduct fecal pellet surveys in absent and low vegetation cover. The ability of UAVs to traverse rough habitat could provide an extensive reduction in field-time and associated survey costs. As such, the relative efficacy of UAV-based pellet surveys must be calibrated for each project with detection rates and reliability evaluated prior to data collection. Researchers must understand the local impact of vegetation cover density on pellet detection.

Our primary UAV-related concern was that propeller wash (air pushed from the rotors) would move pellets or vegetation thus impacting detection. This concern proved unwarranted as we detected no impacts. Our pseudo pellets were often evenly spread throughout plots without being blown to the edges or next to obstacles such as vegetation. This was true even for bare-ground plots with minimal rolling resistance. For studies where this is a concern, researchers should conduct pre-study data collection to determine propeller wash impact.

We believe that UAVs can provide data on small phenomena such as fecal pellet surveys. These can provide flexibility for natural resources agencies conducting critical work with decreasing budgets. The relatively low cost and availability of UAVs and associated components make the adoption of UAV technology a low-risk endeavor for agencies seeking higher returns on investments. We strongly recommend additional evaluation of UAV accuracy in various cover types and scenarios. Additionally, we recommend that UAV operators understand the local, state, and federal laws prior to use of any UAVs. Ultimately, UAVs are like any other research and conservation tool. They will provide quality data if the project design is robust and the limitations of the equipment are understood.

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