Techniques

A rapid assessment function to estimate common raven population densities: implications for targeted management

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Abstract: Common raven (*Corvus corax*; raven) populations have increased over the past 5 decades within the western United States. Raven population increases have been largely attributed to growing resource subsidies from expansion of human enterprise. Concomitantly, managers are becoming increasingly concerned about elevated adverse effects on multiple sensitive prey species, damage to livestock and agriculture, and human safety. Managers could benefit from a rapid but reliable method to estimate raven densities across spatiotemporal scales to monitor raven populations more efficiently and inform targeted and adaptive management frameworks. However, obtaining estimates of raven density is data- and resource-intensive, which renders monitoring within an adaptive framework unrealistic. To address this need, we developed a rapid survey protocol for resource managers to estimate site-level density based on the average number of ravens per survey. Specifically, we first estimated raven densities at numerous field sites with robust distance sampling procedures and then used regression to investigate the relationship between those density estimates and the number of ravens per survey, which revealed a strong correlation ($R^2 = 0.86$). For management application, we provide access to R function software through a web-based interface to estimate density using number of ravens per survey, which we refer to as a Rapid Assessment Function (RAF). Then, using a simulation analysis of data from sites with abundant surveys and the RAF, we estimated raven density based on different numbers of surveys to help inform how many surveys are needed to achieve reliable estimates within this rapid assessment. While more robust procedures of distance sampling are the preferred methods for estimating raven densities from count surveys, the RAF tool presented herein provides a reliable approximation for informing management decisions when managers are faced with resource and small sample size constraints.

Key words: *Centrocercus urophasianus*, common raven, *Corvus corax*, distance sampling, greater sage-grouse, monitoring, nest predators, point-count, rapid assessment, survey protocol

Common ravens (*Corvus corax*; ravens) are native to North America (Boarman and Heinrich 1999). However, since the mid-twentieth century, raven abundance has increased considerably (Sauer et al. 2017), and populations have expanded into previously unoccupied areas. Recent modeling of Breeding Bird Survey data (Sauer et al. 2017) revealed substantial population growth across nearly all ecoregions within the United States and Canada over the course of 53 years (Harju et al. 2021). Most notably, within the Cold Desert ecoregion, which includes the Great Basin, abundances of ravens were predicted to be the highest in relative

Figure 1. Evidence of common raven (*Corvus corax*) depredating eggs captured from video-monitoring project of greater sage-grouse (*Centrocercus urophasianus*) nests in the Great Basin, USA.

abundance and exhibited increases of ~460% (Harju et al. 2021). Other areas also experienced substantial increases in abundance, which included Mediterranean California and Warm Deserts of the southwestern United States. This expansion is commonly occurring on landscapes with increasing human-related resource subsidies (e.g., foraging resources and roosting and nesting structures; Kristan et al. 2004, Boarman et al. 2006, Leu et al. 2008, Bui et al. 2010, Howe et al. 2014), which provide ravens with resources that have led to elevated survival and reproduction rates.

Studies have documented negative effects on sensitive prey species where increasing abundances of ravens have been observed (for review of avian species, see Coates et al. 2021). Of specific concern, effects have been documented for greater sage-grouse (*Centrocercus urophasianus*; sage-grouse; Bui et al. 2010, Coates and Delehanty 2010, Dinkins et al. 2016, Peebles et al. 2017; Figure 1), snowy plovers (*Charadrius nivosus*; Page et al. 2009, Peterson and Colwell 2014, Lau et al. 2021), and Mojave Desert tortoises (*Gopherus agassizii*; Boarman 2003, Kristan and Boarman 2003, Tracy et al. 2004, Holcomb et al. 2021). This body of evidence has substantiated concerns that growing populations of ravens pose a threat to species already challenged by habitat loss, changing climates, disease, and other pervasive threats. Furthermore, increasing numbers of ravens associated with human enterprise and expansion into remote environments may present challenges related to human health and safety as well as eco-

nomic losses (Merrell 2012). For example, large numbers of undeterred perching and nesting ravens on transmission lines have been reported to cause electrical faults (Restani and Lueck 2020), which are interruptions of power that sometimes lead to outages (Short 2005). Ravens have also been reported to damage newborn or young livestock (Larsen and Dietrich 1970).

Despite the reported ecological and societal effects of subsidized and growing populations of ravens, management actions aimed at reversing these effects are challenging, largely because relatively few studies have offered tools to monitor raven populations and help guide when and where management solutions could be most beneficial (Boarman 2003, Boarman et al. 2006, Peebles et al. 2017). One major issue facing resource managers is the time and effort needed to sufficiently survey ravens, to estimate densities accurately, and to track population changes through time, which is imperative to an adaptive management strategy (Dettenmaier et al. 2021). Importantly, current raven densities alone do not provide insight into whether raven densities are at levels considered problematic. In fact, thresholds for implementing management may vary depending on overlap with sensitive species or human enterprises that are affected by increases in ravens. For example, Coates et al. (2020*a*) found raven abundance >0.4 ravens km^{-2} to be associated with below average sage-grouse nest success in the Great Basin, while in the Mojave Desert, where ravens are relatively more abundant, a greater value was identified as a conflict threshold for impacting juvenile desert tortoises (Holcomb et al. 2021). Thus, estimating local level population densities of ravens could be an effective first step to evaluate whether conflict thresholds have been reached or exceeded and inform management actions.

Surveys following management actions are typically needed to assess efficacy of management efforts. However, resource managers often lack resources to obtain adequate numbers of surveys to inform robust analyses using distance sampling that facilitate estimation of "true" abundance. For example, 60 individual observations are recommended as the minimum number necessary to estimate a detection function based on distances of ravens from the observer (Buckland et al. 2001, Kéry and Royle 2015). A consequence of this is that a relatively

large number of surveys is generally required, especially if densities and/or detection probabilities are relatively low, as more surveys are needed to obtain this minimum number of observations. Furthermore, sites may warrant repeated sampling across years to achieve comparable results, as both detectability and abundance vary spatiotemporally (Buckland et al. 2001, Marques et al. 2007). Although robust and intensive study designs that adhere to sample size recommendations for modeling populations of unmarked individuals should be pursued, it is rarely possible to meet these criteria while monitoring effectiveness of all management actions at the scale and frequency needed to guide decision-making within an adaptive management framework. However, this limitation should not discourage all forms of monitoring that can have management utility. Understanding and monitoring local relative raven abundances may still be achieved with relatively small sample sizes of field data.

Our primary goal was to establish a rapid, yet reliable, survey protocol and estimation tool, referred to here as a Rapid Assessment Function (RAF), to estimate density with data that may be inadequate for robust modeling frameworks such as distance sampling analyses. Secondly, we sought to provide guidance regarding the number of surveys necessary to obtain stable results of estimates from the RAF. To accomplish this, we first relied on existing survey data to estimate raven density at numerous study sites within sagebrush ecosystems of the Great Basin region of the western United States using hierarchical distance sampling models that account for detection. We then established a relationship between site-level densities estimated from distance sampling methods and a simple raven index (no. ravens/no. surveys) to approximate modeled raven density (i.e., estimates obtained from distance sampling methods) at defined field units (averaging ~1,400 km²). Third, we developed an R function, R package (Roth et al. 2021*a*), and web-based software (available at https://rconnect.usgs.gov/smart/; Roth et al. 2021*b*) for managers to input the index value and calculate RAF estimates of density with uncertainty from prediction intervals given the modeled relationship established in our second objective. And last, we used an iterative sampling process to test the sensitivity of the RAF

to number of surveys to help guide managers on the effort required to approximate raven density estimates. While this rapid survey and RAF tool cannot substitute for more rigorous study designs using distance-based sampling, it can provide managers with information regarding raven density that can be employed in an adaptive management framework.

Study area

We collected raven point-count data from defined field study site units throughout the northern Great Basin sagebrush-steppe (*Artemisia* spp.) ecosystem of Idaho, Nevada, and portions of Oregon and California, USA (see O'Neil et al. 2018, Coates et al. 2020*a*; Figure 2). The data used to implement a rapid survey index were previously used to predict raven density and its influence on sage-grouse nest success across this study region (Coates et al. 2020*b*). A detailed description of the study area can be found in Coates et al. (2020*a*).

Methods
Data collection

A detailed raven survey protocol is provided in the supplemental material (Appendix A). Briefly, we conducted 30,457 raven survey point-counts from 2007–2019 at 50 field sites distributed across the study area, covering Nevada, Idaho, the eastern Sierra Nevada of California, and eastern Oregon (Appendix B). Field sites averaged 1391.7 km² (range: 42.8–4,739.1 km²; Figure 2). Survey locations occurred within field sites that generally aligned with long-term studies of sage-grouse populations and were conducted entirely within sagebrush ecosystems. Within field sites, raven surveys were conducted at random locations as well as at sage-grouse telemetry locations corresponding to nesting, brood-rearing, and adult locations. We completed most of the surveys between April and August (~95%). Thus, these data also coincided with the reproductive period for sage-grouse as well as numerous other wildlife species, when predation by ravens may have the most effect (Bui et al. 2010). Within 2 field sites (Idaho National Lab within Idaho, and Oregon), survey locations for ravens were revisited intra- and inter-annually. At all other field sites, raven survey locations were not duplicated within or across years. Field sites var-
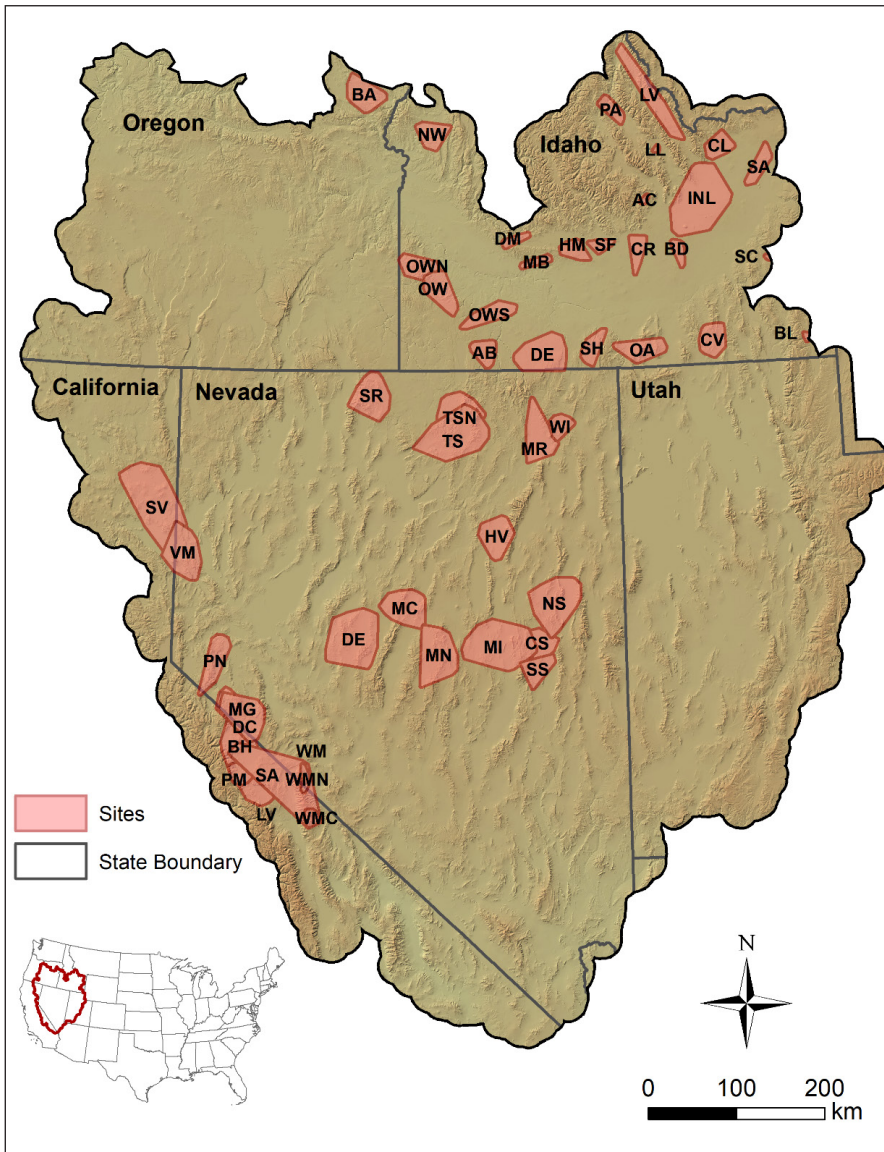
Figure 2. Map of field site units where common raven (*Corvus corax*) surveys were conducted across sagebrush (*Artemisia* spp.) ecosystems within the Great Basin region, USA, 2007–2019. Basemap is the U.S. Geological Survey (USGS) Digital Elevation Model (USGS 2009).

ied in size and proximity to anthropogenic features and included sites monitored in Coates et al. (2020*a*) as well as sites added in more recent years (Appendices B and C). Approximately 56% of the survey data in this study were previously analyzed in Coates et al. (2020*a*). Each individual field site was surveyed at least once during the study. The number of surveys conducted at each field site and year averaged 232 and ranged from 16–770 (Appendix C).

At each survey point, surveyors visually scanned the 360° viewscape for 10 minutes using binoculars and unaided eyes and recorded all ravens they observed. For each observation of a raven or group of ravens, the time, distance, and bearing were recorded using a digital rangefinder, handheld global position system device (Garmin; Garmin International Inc., Olathe, Kansas, USA), and compass, respectively. Observations likely included both breeding and non-breeding ravens (Bui et al. 2010, Coates et al. 2016).

Data analysis

We used hierarchical distance sampling (Buckland et al. 2001, Thomas et al. 2010) to obtain estimates of raven density within sage-grouse habitat across field site units and years using point-count data (Coates et al. 2020*a*). Conventional distance sampling corrects for the probability of detecting an individual or group based on its distance to an observer (Buckland et al. 2001). When enough observations are obtained within a defined area (~60 or more; Buckland et al. 2001), a distance detection function adjusts for imperfect detection at increasing sampling distance (e.g., failure to observe birds that are present) and reliable estimates of density can be inferred from the counts. The inclusion of detection covariates, with respect to the scale parameter in either a half-normal or hazard rate detection function, can improve estimates by quantifying factors that influence detection and thereby improve the accuracy of the detection function (Marques et al. 2007). For our analyses, we estimated the detection function $\hat{g}[r, z]$ for point-count data, where the probability of detecting ≥1 raven is conditional on distance (r) from the center of a survey point as well as the vector of possible covariates z (Buckland et al. 2001, Marques et al. 2007, Rivera-Milán et al. 2015).

Distance model. We used the "unmarked" package (Fiske and Chandler 2011) in R 3.5.0 (R Development Core Team 2018) to estimate raven density for each field site and year combination using generalized distance sampling models for point-count survey data (Royle et al. 2004, Sillett et al. 2012). We followed methods in Coates et al. (2020*a*), where observations of ravens were truncated at 1.125 km, beyond which probability of detection was <0.1 (Buckland et al. 2001, Burnham et al. 2004), and distances were binned into 5 equal distance classes (Sillett et al. 2012, Kéry and Royle 2015, Coates et al. 2020*a*). We specified a half-normal distance detection function to evaluate the effect of distance on detection probability (Thomas et al. 2010, Fiske and Chandler 2011). When estimating the detection function parameters, we pooled surveys with those of neighboring field sites under rare occasions where too few observations were present to reliably estimate a detection function (Appendices B and C; Coates et al. 2020*a*). We fit area of viewshed and percent

of forested covariates on the detection function, quantified as zonal means within the effective truncation distance (radius = 1.125 km). We modeled density using a negative binomial distribution. We specified field site and year as covariate effects influencing abundance (Royle et al. 2004, Sillett et al. 2012) to derive densities for each field site and year combination (Sillett et al. 2012, Kéry and Royle 2015). We include a histogram of raw binned distances across all site-years, as well as detection curves for each site-year (Appendix Figure C.1). Each field site-year distance sampling estimate of density (hereafter, D) was then assumed to represent its "true" value for the purpose of evaluating an index that could potentially approximate these densities under less rigorous sampling designs.

Raven density index for rapid assessment. We explored the use of a RAF to approximate modeled raven densities under circumstances where the number of surveys carried out at a specific study area would not meet sample size requirements for conventional distance sampling. Specifically, by leveraging information from the modeling efforts that were previously completed, for each site-year combination, we computed the ratio of total number of ravens observed to total number of point-count surveys performed (i.e., raven index) for a site-year and related this to the corresponding raven density estimate obtained from hierarchical distance sampling. We applied a simple linear regression model where the response variable was the log-transformed raven density estimate and the predictor variable was the log-transformed raven index (n ravens observed*site-year* / n surveys*site-year*). Log-transformations were performed to account for heteroskedasticity in the modeled relationship (variance increases as counts increase). We measured the ability of the raven index to explain D at each field site by calculating R^2. We report the coefficients from this model, which were used to develop the RAF, along with an associated R function (v 3.5.0; R Development Core Team 2018; Appendix D), which obtains predictions of raven density ±95% prediction interval (RAF density). We implemented prediction intervals to capture the possible range of future measurements. While distance sampling methods are preferred for estimating raven density when survey sample sizes are adequate, we reasoned that this function and its associated index could

Table 1. Coefficients from linear model results of the relationship in error in raven density estimates to number of surveys and estimated common raven (*Corvus corax*; raven) density. For each of 39 site unit-years with >300 surveys, density estimates were derived for different numbers of surveys by iteratively subsampling from the surveys within a given site, using successively fewer and fewer samples and re-evaluating density given the raven index equation. Error was calculated as the difference in density using all survey data from the density using the subsampled surveys.

Model	Intercept (SE)	β_D (SE)	β_{ns} (SE)	$\beta_{D:ns}$ (SE)	ΔAIC
$\widehat{D}*ns + \widehat{D} + ns$	-0.327 (0.004)	0.739 (0.005)	0.001 (0.00002)	-0.0032 (0.00004)	0.0
$\widehat{D}$	-0.183 (0.003)	0.412 (0.005)			5165.8
$\widehat{D}+ns$	-0.186 (0.004)	0.412 (0.005)	0.00002 (0.00002)		5166.6
ns	-0.010 (0.005)		0.00004 (0.00003)		11317.6
Null	-0.004171 (0.002270)				11317.7

provide a method of approximation at study sites subject to small sample size constraints that are geographically similar to the sites used to generate the index.

Sensitivity to number of surveys. While a minimum of ~60 detections has been recommended for estimating the distance-detection function from distance sampling models (Buckland et al. 2001), little guidance exists for determining the minimum number of surveys needed to provide reliable estimates of density (*D*), particularly when surveys are stratified across multiple sites and years. With nearly 30,000 surveys overall, we tested the sensitivity to sample size across all our site-years with >300 point-counts (*n* = 39). We chose 300 surveys because this ensured we had the recommended number of observations for distance sampling (i.e., 60 observations; Buckland et al. 2001), even at sites with low densities. Because we sought to evaluate the estimates of density from the RAF as proxy for distance-based density estimates, we assumed that any given estimate from the RAF was unbiased. However, at a very small number of surveys, many birds go undetected, which could result in a predominance of zero-counts at low numbers of surveys, particularly for low-density sites. This could result in negative bias in density estimates for sites with low numbers of surveys. Thus, we sought to explore bias at very low sample numbers and estimate how many surveys were necessary for uncertainty to stabilize by evaluating asymptotic behavior in the uncertainty around predicted density ($\widehat{D}$; standard error and 95% confidence intervals) corresponding with numbers of surveys.

To explore relationships between $\widehat{D}$ and number of surveys (*ns*), for each site-year with >300 surveys (Appendix C), we calculated $\widehat{D}$ using the RAF (Appendix D) and iteratively subsampled from the surveys within a given site, using successively fewer and fewer samples (Marques et al. 2007, Buckland et al. 2016). First, we randomly sampled from the site-year survey data ($n_{sub} = n$, *n-1*, *n-2*, … , *n-n+1*). Second, within each subset, we randomly sampled the raven counts with replacement to represent the variation in counts occurring within the subset. We drew 10,000 bootstrap samples to generate the standard error and 95% confidence intervals around $\widehat{D}$ for each subsample. For each site-year, we also calculated density using the RAF with all survey data ($\widehat{D}_{FULL}$). For each subsample, we then calculated the log-transformed ratio of $\widehat{D}$ to $\widehat{D}_{FULL}$. Additionally, we calculated the absolute difference of $\widehat{D}$ from $\widehat{D}_{FULL}$ for each subsample and averaged across all site-years to obtain an average absolute error for each *ns*.

By subsampling survey data, we calculated error in RAF estimates as deviation in estimates using subsampled survey data from those using the complete data from each site ($\widehat{D}$ minus $\widehat{D}_{FULL}$). Using a linear model, we then estimated the relationship between error in RAF estimates with number of surveys and $\widehat{D}$. Positive values of error reflect overestimation of density, whereas negative values reflect underestimation of density with respect to $\widehat{D}_{FULL}$. We considered both additive effects and interactive effects of $\widehat{D}$ and *ns* on error. Models were carried out using R 3.5.0 (R Development Core Team 2018), and best model was chosen using Akaike informa-
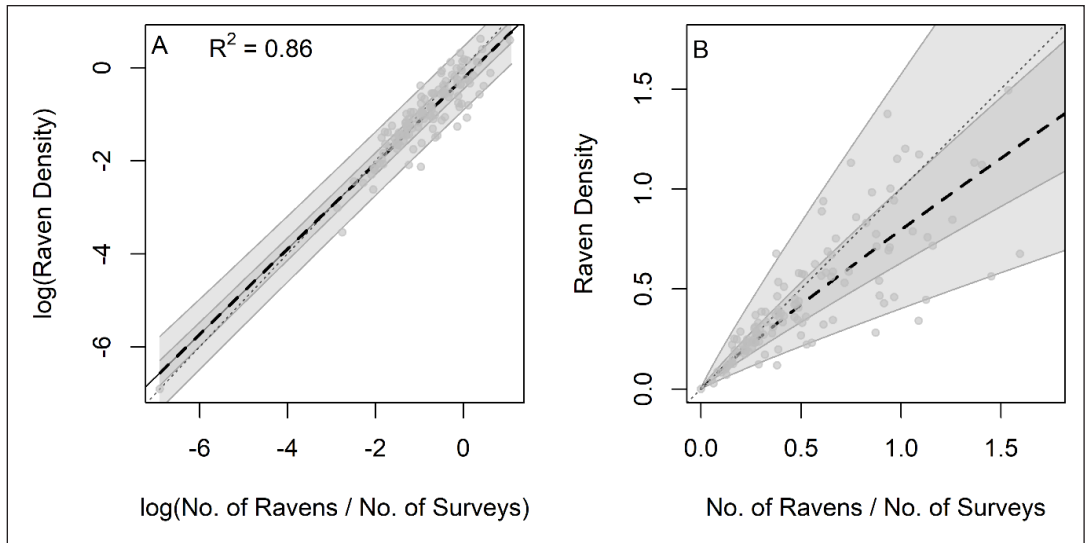
Figure 3. Relationship between site- and year-specific estimates of common raven (*Corvus corax*; raven) density from distance sampling models (ravens × km^{-2}) and the average number of ravens observed per survey at the corresponding site-years. Figure (A) represents the log-transformed data, while (B) represents back-transformed estimates, which reflects output from the RAF. Points represent individual site-year estimates. Light gray shading represents 95% prediction interval and dark gray shading represents 50% prediction interval. Dashed gray line represents a 1:1 relationship.

tion criterion (AIC). We report the coefficients with standard error (SE) from the best model (Table 1). Additionally, we added a calculation of error given sample size and $\widehat{D}$ to the RAF.

Results

We detected 16,050 ravens (distance ≤1,125 m) at 30,457 point-count surveys across 50 field sites in the Great Basin, 2007–2019 (Table S2-1). Of all surveys conducted, we detected ravens at 6,555 survey locations (21.5%). Raven density estimates ranged from 0.00–1.86 ravens per km^{-2} ($\bar{x} = 0.463$, SD = 0.349) across all field sites and years of the study (Table S2-2).

Raven density index for rapid assessment

Raven density corresponded closely to average number of ravens detected per survey (raven index) within each field site unit (distance ≤1,125 m) with values of 0.00–2.889 ($\bar{x} = 0.546$, SD = 0.430; Table S2-2). We found a strong association between the distance-based model estimate and the raven index ($R^2 = 0.858$). This indicated that raven density estimates from distance sampling could be approximated by the raven index ($\hat{\beta}_{\log(\text{ravens/survey})} = 0.917$, SE($\hat{\beta}$) = 0.033; Figure 3; Appendix C).

Sensitivity to number of surveys

Based on simulation analyses, estimates of raven density calculated from the RAF were biased low on average at low sample sizes, while uncertainty in the estimate remained high at sample sizes <50 (Figure 4). The average absolute difference of $\widehat{D}$ from $\widehat{D}_{FULL}$ began to stabilize between 50 and 100 surveys (Figure 4B).

We found that the model that best described sample-size dependent error ($\widehat{D}$ - $\widehat{D}_{FULL}$) included an interaction effect of $\widehat{D}$ and number of surveys (ΔAIC = 5,165.8 from the next best model). Specifically, we found a positive relationship between error and $\widehat{D}$ ($\beta_D = 0.739$ [SE = 0.005]) where high estimated density resulted in greater overestimation of raven density and low estimated density resulted in greater underestimation of raven density. However, this relationship was dependent on number of surveys ($\beta_{D:ns}$ = -0.0032 [SE = 0.00004]; Table 1; Figure 5).

Discussion

Increasing populations of ravens subsidized by anthropogenic resources and development represent a novel threat to sensitive prey species within semi-arid western ecosystems of North America. Nesting species at lower trophic levels may be vulnerable to spillover
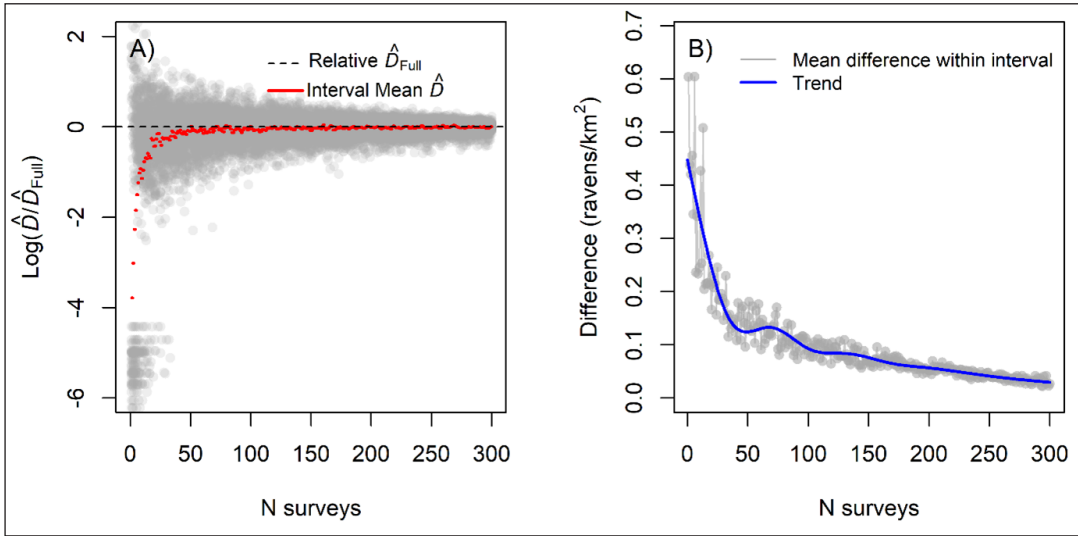
Figure 4. Ratio of estimated common raven (*Corvus corax*; raven) densities using subsampled survey data to estimated density using all surveys from each site unit-year (A), and absolute difference of density calculated using all surveys from estimated densities using subsamples (B), corresponding to number of surveys. Uncertainty was measured by iteratively subsampling from the original point-count data and re-evaluating density given the raven index equation for each of 39 site unit-years with >300 surveys.
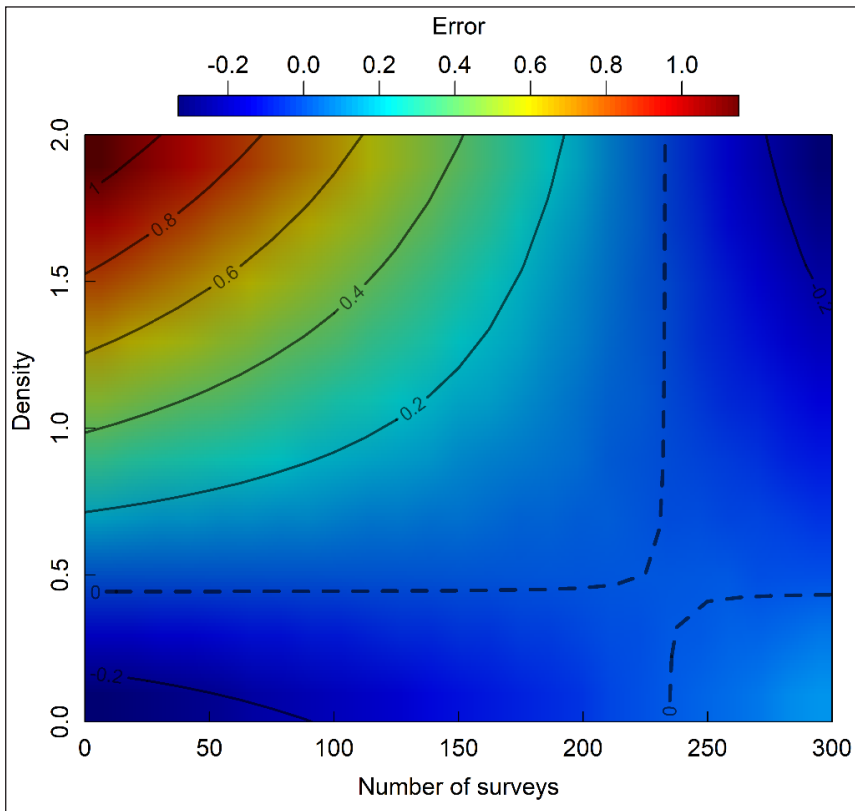
Figure 5. Relationship between error in estimated common raven (*Corvus corax*; raven) density and number of surveys conducted across estimated raven densities. For each of 39 site unit-years with >300 surveys, density estimates were derived for different number of surveys by iteratively subsampling from the surveys within a given site unit-year, using successively fewer and fewer samples and re-evaluating density with the raven index equation.

(Kristan and Boarman 2003, Oro et al. 2013) or hyperpredation effects (Smith and Quin 1996) because ravens are opportunistic and prey-switch with ease (Boarman and Heinrich 1999). These threats suggest that monitoring range expansion and population trends of ravens is likely to be an essential element of conservation and management plans for sensitive prey species, especially as anthropogenic development continues to expand in remote areas (Restani et al. 2001, Kristan and Boarman 2007, O'Neil et al. 2018). By providing a sampling protocol (Appendix A), a simple index approach, and a Rapid Assessment Function (Appendix D) to estimate density of local populations using feasible point-count survey efforts, our objective was to advance land managers' and biologists' capacity to monitor and respond to changing predator communities to conserve sensitive species. The relationship established between the raven index (n ravens/n surveys) and estimates of density from more rigorous distance sampling methods ($R^2 = 0.86$) was developed from intensive survey efforts occurring throughout sagebrush ecosystems of the Great Basin region of the United States. The RAF uses this estimated relationship to account for detection probability of ravens within sagebrush ecosystems, serving as a correction factor on the raven index, and was reliable in its ability to estimate raven density with fewer surveys than distance-based modeling necessitates. As such, the RAF is the function we developed that allows users to estimate density using n ravens/n surveys, which can support baseline monitoring of local raven populations given efforts of 50–100 point-count surveys to obtain an estimate for regions of interest consistent in size with those in this study (~1,400 km²).

While estimates from point-count surveys of ravens based on distance-based models provide precise and unbiased estimates for a site, land managers following our sampling protocol (Appendix A) can apply the RAF in situations where survey data are limited or insufficient for distance sampling methods. This allows for more efficient assessment of trends and evaluation of the effectiveness of management actions when resources are limited. For example, it has been posited that 60 observations are necessary to estimate detection probability using distance-based methods. Given the average proportion of surveys where ravens were detected in this study across sites and years (0.22, or about 1 out of every 5 surveys) and an average of 1.39 individual observations at surveys where ravens were detected, it would take ~195 surveys to reach this minimum. Because the RAF bypasses the need to directly estimate detection probability based on observations, our analysis suggests that efforts may not need to exceed ~100 surveys to achieve acceptable precision; for all sites where we conducted simulations, minimal gains in precision were achieved at larger numbers of surveys. In fact, the RAF can estimate density based on any number of surveys, provided managers use caution when interpreting results from small numbers of surveys. Reducing survey effort would alleviate some burden on managers and could make local-scale raven population assessment more efficient. To further streamline trend monitoring, we provide an R function (Appendix D; R package [Roth et al. 2021a]) and web-based software (available at https://rconnect.usgs.gov/smart/; Roth et al. 2021b) that facilitates rapid estimation of the raven density from the RAF by simply entering (1) how many surveys were conducted and (2) the total number of ravens observed. While it remains best practice to collect sufficient data for implementation of distance sampling models (Buckland et al. 2001), being able to quickly assess raven populations within smaller defined areas is critical for management of sensitive prey species that are likely vulnerable to raven predation (Dettenmaier et al. 2021).

Important considerations for the use of this tool are the spatial and temporal distribution of surveys. The sites within this study ranged from 42.8–4,739.1 km². The average number of surveys per 100 km² was ~12.0 (SE = 1.7), with larger sites generally consisting of higher numbers of surveys because more were needed to adequately sample larger areas (Appendix B). While many survey locations within this study were associated with sage-grouse telemetry locations, we also included random locations throughout study sites to incorporate variation in landscape characteristics. For example, while sage-grouse might tend to be located within more rural areas, ravens utilizing nearby anthropogenic subsidies must also be accounted for. Raven surveys must be randomly situated around study sites and must incorporate re-

mote regions within the study area (where ravens numbers may be relatively low) as well as areas in proximity to anthropogenic subsidies, which ravens may utilize for nesting and foraging areas. Within this study, 95% of surveys took place during the reproductive season for both sage-grouse and ravens. During the reproductive season, breeding ravens are largely confined to an area ~1500 m around their nest, whereas non-breeding (or transient) ravens are less territorial and forage across a larger area (Harju et al. 2018). Following nesting, breeding ravens behave similarly to non-breeding ravens and rely more heavily on anthropogenic subsidies for foraging (Harju et al. 2018). Thus, groups of ravens might be more likely to be observed after nesting season concludes or during the nesting season in areas with important foraging or water sources for non-breeding ravens. Understanding the population structure of ravens as well as temporal and spatial dynamics of ravens at a site will be imperative for balancing efforts at sites and within and across years.

By subsampling survey data, we estimated deviation in the RAF estimates from those using the complete data from each site as a function of sample size (number of surveys) to inform the minimum number of surveys needed to obtain stable estimates from the method. Importantly, this analysis was dependent on the assumption that density estimates using the full dataset from each site were unbiased estimates. Specifically, the RAF overestimated density when low numbers of surveys occurred at sites with high density, such as those with more availability of subsidies, where the likelihood of detecting a raven or group of ravens at a single survey was higher. These areas might be subject to more variation in raven density estimates, and thus, more surveys would be needed to balance out observations. Conversely, at low density sites, there was a higher likelihood of zero-count surveys, and the RAF underestimated density with low numbers of surveys. Importantly, the potential for underestimation is only as high as the true density, whereas the potential for overestimation can be large, especially in areas where large groups of ravens may be observed, such as areas with large groups of transient ravens. This trend further illustrates the importance of balanced spatial and temporal distribution of

surveys. At higher numbers of surveys, RAF estimates were unbiased under the assumption that the RAF prediction from the full number of surveys represented the true value (i.e., the best fit to estimates from distance sampling models). Further analyses and validation based on precision and power from distance sampling model results will improve the utility of such rapid assessments and can be used to update the RAF approach.

Within the RAF, we incorporated an option for a correction factor on the 95% confidence intervals to incorporate uncertainty associated with varying densities and effort across sites and years so that users of the tool are aware of sources of uncertainty when developing management plans based on raven density. Confidence in density estimates may help facilitate empirical-based decisions made by land and wildlife managers regarding prescription of management practices (Dettenmaier et al. 2021). For example, if density thresholds drive the decision to pursue management actions, incorporating the secondary error term would provide the most conservative estimates of variance in raven density. Where high levels of uncertainty in density exist, managers might conduct additional raven surveys to gain confidence in estimates before targeting management actions.

This approach was developed in a sagebrush steppe ecosystem and does not capture variation in detectability that may occur within different ecosystems, sites, over time, and among observers. Variation in detection that is not captured in distance sampling models is likely the main cause of deviation away from "true" density estimates. Furthermore, variation in detectability is the most likely reason for the RAF estimate to deviate from the distance sampling density estimate (Figure 3), which is especially problematic in locations that are different from the system where the index was derived. For example, ravens are conspicuous in relatively open habitats, whereas habitats characterized by dense vegetation (i.e., forests) or areas with more limited viewshed may have reduced detectability of ravens. Because our distance models do not account for reduced detection probability (i.e., the ability to see a raven given that it is present) in such habitats, the RAF may underestimate raven density in those areas. More rigorous distance data would be required

to estimate raven detection more accurately in areas with restricted visibility. However, we believe the RAF in this study can be used in open habitats with some heterogeneous topography that share similar characteristics to sagebrush ecosystems.

Management implications

Increasing evidence of raven effects on multiple sensitive species (Coates et al. 2021) reinforces the need for adaptive management strategies and rapid assessment protocols for ravens within ecosystems where predator–prey conflicts exist. We anticipate that monitoring raven population trends will continue to be an important component of conservation and management plans for the numerous wildlife prey species that are likely to be affected, especially as widespread anthropogenic development continues to accelerate in remote areas. By estimating a simple index and using it to calculate density using our RAF estimation approach for rapid assessment of local populations, we have advanced the capabilities of land managers and biologists to monitor and respond to changing predator communities.

Acknowledgments

Supplemental material

Supplemental material can be viewed at https://digitalcommons.usu.edu/hwi/vol15/iss3/16.

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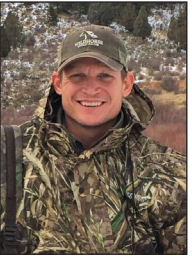
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