Supporting Information

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**S6. Precision of Deer Abundance and Density Estimates**

**Methods**

We calculated the coefficient of variation (CV) for estimates accompanied by a measure of precision (i.e., SD, SE, CI, or CrI):

$CV=\frac{SD}{\hat{N}} $,

where *SD* is the standard deviation (derived from the reported SE, CI, or CrI when not directly available) and $\hat{N}$ is the estimated abundance or density (Thompson et al. 1998). The CV is a measure of relative precision (i.e., is independent of the absolute value of the estimate) that can be compared among estimates (e.g., Daniels 2006). The smaller the CV, the more precise the estimate and the more useful it is.

Given that CVs are positive real numbers, we used a generalized linear model (GLM) with a Gamma family with a log-link to test the effects of the 9 explanatory variables on relative precision: method, year of data collection, study area size (ha), management (yes or no), deer density, elevation, human influence, tree cover, and net primary productivity. For further details on the biophysical and anthropogenic variables, see Supporting Information S1. Management was defined as yes for a clearly articulated management objective (Supporting Information S3) or no for otherwise. We grouped the estimates into second-order methods (method) containing ≥30 estimates for which CVs could be calculated. We used a stepwise model selection approach to identify the important explanatory variables, removing one variable at a time from the full model (Murtaugh 2009). For each step, we selected the best model based on the lowest Akaike’s Information Criterion corrected for small sample sizes (AIC*c*; Burnham and Anderson 2002). This was repeated until the removal of any additional explanatory variable resulted in a higher AIC*c* value. Analyses were performed using R version 4.0.2 (R Core Team 2020). The data and code that support the findings of this study are openly available in figshare at <https://doi.org/10.6084/m9.figshare.18846647.v1> (Forsyth et al. 2022).

**Results**

For the 1,247 estimates for which CVs could be calculated, 87.8% could be included within 5 first-order methods and 14 second-order methods (Table S6.1). The remaining 152 estimates were either from a category with <30 estimates, or there was insufficient methodological information in the publication for it to be included in one of the second-order methods. The best model explaining the precision of the CVs included all predictors except net primary productivity (Tables S6.2 and S6.3).

The precision of estimates declined from 0.42 in 1980 to 0.83 in 2017 (Fig. S6.1). Estimates from studies with a management objective were on average less precise (mean CV = 0.76; 95% CI, 0.52–1.11) than estimates from research studies (mean CV = 0.51; 95% CI, 0.38–0.68). Study area size, deer density, and elevation had the strongest effects on the precision of the estimates. The precision of estimates declined with increasing study area size and elevation, and increased with increasing deer density. Increases in human influence and tree cover were associated with small decreases in precision.

Of the 1,247 estimates for which the CV could be calculated, only 329 (26.4%) were ≤0.25, a commonly used rule-of-thumb threshold for assessing whether estimates will be useful for research and management (Skalski et al 2005). Neither the median nor the 2.5th percentile of any of these 14 methods was below 0.25 (Fig. S6.2, Table S6.3). All 5 first-order methods were characterized by very long tails, with CVs >4.00, to a maximum of 9.34 for walked direct counts (Fig. S6.2).

The most precise estimates were provided by analyzing motion-sensitive camera data using capture–recapture methods, and by spotlight counts from a vehicle with or without using distance sampling (Table S6.1, Fig. S6.2). Pedestrian direct visual counts, diurnal vehicular direct counts, and fecal pellet counts were the least precise methods. In general, accounting for heterogeneity in detection probabilities resulted in more precise estimates, like capture–recapture analysis for motion-sensitive cameras and distance sampling for fecal pellet counts. Nocturnal vehicular direct counts provided more precise estimates than diurnal counts, but thermal imagery estimates were less precise than spotlight estimates. For aerial counts, capture–recapture estimates were more precise than estimates from distance sampling or double counts.

**Table S6.1.** Classification by second-order method (*n* ≥30) of the 1,095 estimates of deer abundance or density in articles published during 2004–2018 for which the CV could be calculated.

|  |  |  |  |
| --- | --- | --- | --- |
| Method | *n* | Mean CV | 95% CI |
| First order | Second order |
| Fecal pellet | Pellet count | 240 | 0.99 | 0.80–1.23 |
|  | DNA capture–recapture | 34 | 0.80 | 0.56–1.15 |
|  | Distance sampling | 62 | 0.63 | 0.46–0.87 |
|  |  |  |  |  |
| Motion-sensitive cameras | Individual count | 73 | 0.64 | 0.47–0.88 |
|  | Capture–recapture | 72 | 0.39 | 0.29–0.51 |
|  |  |  |  |  |
| Pedestrian direct | Visual counts | 132 | 1.03 | 0.80–1.33 |
| counts | Drive count | 35 | 0.74 | 0.51–1.06 |
|  |  |  |  |  |
| Vehicular direct | Diurnal | 40 | 1.09 | 0.77–1.54 |
| counts | Thermal imagery | 110 | 0.68 | 0.52–0.89 |
|  | Spotlight | 69 | 0.36 | 0.27–0.49 |
|  | Spotlight distance sampling | 44 | 0.41 | 0.30–0.58 |
|  |  |  |  |  |
| Aerial direct | Distance sampling | 61 | 0.70 | 0.43–1.14 |
| counts | Double observer | 87 | 0.74 | 0.55–1.01 |
|  | Capture–recapture | 45 | 0.48 | 0.35–0.65 |

**Table S6.2.** Summary of the stepwise selection process identifying the best model explaining the relative precision of deer abundance or density estimates in articles published during 2004–2018. Method refers to the second-order methods listed in Table S6.1. For each step, the best model is shown in bold, with the overall best model in step 2. AIC*c*: Akaike Information Criterion corrected for small sample size. *wi*: model weight.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Modela | df | logLik | AIC*c* | ΔAIC*c* | *wi* | Pseudo *R*2 |
| Step 1: |  |  |  |  |  |  |
| Method + management + year + area + density + elev + GHII + tree + NPP | 23 | –496 | 1,038 | 1 | 0.32 | 0.42 |
| Method + management\*year + area + density + elev + GHII + tree + NPP | 24 | –496 | 1,040 | 3 | 0.12 | 0.42 |
| **Method + management + year + area + density + elev + GHII + tree** | **22** | **–496** | **1,037** | **0** | **0.56** | **0.42** |
| Method + management + year + area + density + elev + GHII + NPP | 22 | –520 | 1,084 | 47 | 0.00 | 0.39 |
| Method + management + year + area + density + elev + tree + NPP | 22 | –564 | 1,173 | 136 | 0.00 | 0.34 |
| Method + management + year + area + density + GHII + tree + NPP | 22 | –513 | 1,071 | 34 | 0.00 | 0.40 |
| Method + management + year + area + elev + GHII + tree + NPP | 22 | –504 | 1,053 | 16 | 0.00 | 0.41 |
| Method + management + year + density + elev + GHII + tree + NPP | 22 | –506 | 1,056 | 19 | 0.00 | 0.41 |
| Method + management + area + density + elev + GHII + tree + NPP | 22 | –501 | 1,048 | 11 | 0.00 | 0.41 |
| Method + year + area + density + elev + GHII + tree + NPP | 22 | –501 | 1,047 | 10 | 0.00 | 0.41 |
|  management + year + area + density + elev + GHII + tree + NPP | 10 | –708 | 1,436 | 398 | 0.00 | 0.17 |
|  |  |  |  |  |  |  |
| Step 2: |  |  |  |  |  |  |
| **Method + management + year + area + density + elev + GHII + tree** | **22** | **–496** | **1,037** | **0** | **0.98** | **0.42** |
| Method + management + year + area + density + elev + GHII | 21 | –520 | 1,082 | 45 | 0.00 | 0.39 |
| Method + management + year + area + density + elev + tree | 21 | –565 | 1,172 | 135 | 0.00 | 0.34 |
| Method + management + year + area + density + GHII + tree | 21 | –513 | 1,069 | 32 | 0.00 | 0.40 |
| Method + management + year + area + elev + GHII + tree | 21 | –506 | 1,054 | 17 | 0.00 | 0.41 |
| Method + management + year + density + elev + GHII + tree | 21 | –506 | 1,055 | 18 | 0.00 | 0.41 |
| Method + management + area + density + elev + GHII + tree | 21 | –502 | 1,046 | 9 | 0.01 | 0.41 |
| Method + year + area + density + elev + GHII + tree | 21 | –502 | 1,046 | 9 | 0.01 | 0.41 |
|  management + year + area + density + elev + GHII + tree | 9 | –711 | 1,440 | 403 | 0.00 | 0.17 |

aElev: elevation. GHII: Global Human Influence Index. NPP: net primary productivity.

**Table S6.3.** Coefficients from the best model (see Table S6.2) explaining the relative precision of deer abundance or density estimates in articles published during 2004–2018. CR: capture–recapture.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Estimate | SE | *Z*-value | *P*-value |
| Intercept: aerial C–R | –38.330 | 12.290 | –3.1 | 0.002 |
| Method aerial double observer | 0.437 | 0.206 | 2.1 | 0.034 |
| Method aerial distance sampling | 0.389 | 0.282 | 1.4 | 0.168 |
| Method motion-sensitive camera count | 0.295 | 0.206 | 1.4 | 0.152 |
| Method motion-sensitive camera C–R | –0.215 | 0.186 | –1.2 | 0.247 |
| Method vehicular spotlight count | –0.274 | 0.191 | –1.4 | 0.152 |
| Method vehicular spotlight distance sampling | –0.141 | 0.204 | –0.7 | 0.490 |
| Method vehicular thermal count | 0.355 | 0.189 | 1.9 | 0.060 |
| Method vehicular diurnal count | 0.825 | 0.218 | 3.8 | <0.001 |
| Method walked drive count | 0.432 | 0.221 | 2.0 | 0.051 |
| Method walked visual count | 0.768 | 0.177 | 4.3 | <0.001 |
| Method fecal pellet count | 0.732 | 0.163 | 4.5 | <0.001 |
| Method fecal pellet distance sampling | 0.276 | 0.197 | 1.4 | 0.161 |
| Method fecal pellet DNA C–R | 0.519 | 0.218 | 2.4 | 0.017 |
| Year | 0.018 | 0.006 | 3.0 | 0.003 |
| Management (no relative to yes) | –0.399 | 0.127 | –3.1 | 0.002 |
| Area | 0.063 | 0.016 | 4.0 | <0.001 |
| Density | –0.080 | 0.020 | –4.0 | <0.001 |
| Elevation | 0.000 | 0.000 | 5.5 | <0.001 |
| GHIIa | 0.006 | 0.003 | 2.0 | 0.051 |
| Tree | 0.001 | 0.001 | 0.9 | 0.359 |

aGHII: Global Human Influence Index.

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**Figure S6.1.** Effects of explanatory variables included in the best model explaining the relative precision of 1,095 deer abundance or density estimates in articles published during 2004–2018.

 **Figure S6.2.** Relative precision of deer abundance and density estimates for first- and second-order methods (the latter with ≥30 estimates; i.e., Figure 5 in the main manuscript but without right-truncation) in articles published during 2004–2018. There were insufficient harvest data estimates with a CV to include this first-order method. Violin plots summarize all estimates for each of the 5 highest-order methods. Bar plots are outputs from the GLM, with circles indicating mean values and blocks indicating the 95% range of the estimates. Sample sizes are in parentheses. The dashed vertical line indicates the value of 0.25, a commonly used threshold for assessing whether estimates will be useful for research and management.

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