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Trade-off assessments between reading cost and accuracy measures for digital camera monitoring of recreational boating effort

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ABSTRACT

Digital camera monitoring is increasingly being used to monitor recreational fisheries. The manual interpretation of video imagery can be costly and time consuming. In an a posteriori analysis, we investigated trade-offs between the reading cost and accuracy measures of estimates of boat retrievals obtained at various sampling proportions for low, moderate and high traffic boat ramps in Western Australia. Simple random sampling, systematic sampling and stratified sampling designs with proportional and weighted allocation were evaluated to assess trade-offs in terms of bias, accuracy, precision, coverage rate and cost in estimating the annual total number of powerboat retrievals in 10,000 jackknife resampling draws. The relative standard error (RSE ± standard deviations) obtained by the sampling designs for sampling proportions from 0.4 onwards were below a 20% threshold for three of the sampling designs across the three boat ramps. Coverage rates of over 90% were observed for the confidence intervals for the estimated annual number of powerboat retrievals, with low relative standard errors (RSE < 20%). Interpreting 40% of camera footage within a year provided the minimum level to obtain sufficient accuracy measures for all sampling designs considered. The stratified random sampling design with weighted allocation consistently resulted in the smallest variance for estimates of annual powerboat retrievals across the various sampled proportions. These findings have the potential to considerably reduce the cost of manual data interpretation, since operating cost increased linearly with increasing sampling proportion.

1. Introduction

Recreational fisheries typically occur over large spatial areas, and activities are subject to considerable temporal variation (Flynn et al., 2018). Managers require robust surveys to provide reliable estimates of fishing effort and catch levels. The use of digital camera (also referred to as remote camera) monitoring is increasingly being used to monitor recreational fisheries. Digital camera monitoring capabilities extend beyond short-term on-site surveys (Hartill et al., 2019; Smallwood et al., 2012), providing the opportunity to obtain reliable estimates of effort and complementary information to assist with the estimation of recreational catch (Hartill et al., 2016; Taylor et al., 2018a; van Poorten et al., 2015). As estimates of fishing effort are obtained from the counts of boats or fishers identifiable in the camera footage, it is necessary to adjust for non-fishing activity (Taylor et al., 2018a) or fishing activity that occurs outside the camera’s field of view (Hartill et al., 2019; Stahr and Knudsen, 2018; van Poorten et al., 2015). Therefore, digital camera monitoring is increasingly being used in conjunction with on-site surveys to address fishery-specific management objectives (Hartill et al., 2019; Taylor et al., 2018a).

Manual interpretation of camera data requires budgets that can be substantial, particularly when cameras are used across multiple sites (Smallwood et al., 2012; Steffe et al., 2017). The largest cost in existing digital camera surveys relates to the manual interpretation of camera footage (Hartill et al., 2019). Thus, in managing the utility of digital camera monitoring, the sampling strategy for reading camera footage needs to reflect budgetary constraints and survey objectives (Steffe et al., 2017). Standard operating procedures have been established for remote camera surveys, ranging from the reading of a full 12-months of camera data during supplementary access point surveys through to low-level monitoring schemes (Steffe et al., 2017). Low-level monitoring schemes ultimately reduce the cost of manual interpretation for digital camera surveys of recreational fishing (Hartill et al., 2016). However, it is not currently known how the accuracy measures of estimates of

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boating effort (here defined as the number of powerboat retrievals) obtained from the various sampling schemes compare to actual counts obtained from reading all recorded camera footage. In effect, investigating the cost-accuracy trade-off could provide evidence-based guidelines by quantifying the relationships between estimates, cost and sampling proportions.

The application of sampling techniques is widespread in different research areas including fisheries surveys (Hartill et al., 2016; Kimura and Somerton, 2006; Yu et al., 2012). The majority of published digital camera studies of recreational fisheries have used some form of stratified random sampling (Table 1). For example, Hartill et al. (2016) determined an appropriate sample size allocation using a stratified random sampling design for camera data obtained from monitoring boat traffic at multiple ramps in New Zealand. However, the performance of stratified random sampling in relation to other types of design has not received much attention. Therefore, it remains largely unknown whether other types of design would be more suitable for digital camera studies.

In Western Australia, there is a network of 28 cameras monitoring 30 fields of view along a coastal stretch of 12,889 km (Hartill et al., 2019). Total expenditure of reading camera footage extends into the tens of thousands of dollars (Steffe et al., 2017). In addition, the levels of boating traffic vary markedly among those locations monitored by digital cameras. We investigated the trade-offs between the cost of manually reading camera data and accuracy measures of sampled data, illustrated through three sets of camera data in Western Australia. The study design was an a posteriori study, implying that the findings were based on existing monitoring information on recreational boating effort. We assessed and compared different sampling designs for a ‘low’, ‘medium’ and ‘high’ use boat ramp, to assist in determining how many days of camera footage should be interpreted and the associated uncertainties. Four sampling designs were considered: simple random sampling (SRS), systematic sampling (SSRS), stratified random sampling with proportional allocation (SRSP), and stratified random sampling with weighted allocation (SRSW). The overarching goal was to accurately estimate the average daily number and annual number of powerboat retrievals at the three boat ramp locations. Outcomes of this work will be used to inform the ongoing reading of camera data for Western Australian recreational fishing surveys in addition to the growing number of studies using digital cameras.

### Table 1
Summary of the sampling design and sampling fractions used for digital camera studies on recreational fisheries.

| Field of view | Sampling design | Study duration | Primary sampling unit | Sampling fraction | Reference |
|---------------|----------------|----------------|-----------------------|------------------|-----------|
| Boat ramps    | Stratified random sampling | 25th Dec 2004 – 24th Dec 2005 | 24-h day | –18 % | Hartill et al. (2016) |
| Artificial reef | Stratified random sampling | 730 days | 24-h day | –32 % | Keller et al. (2016) |
| Foreshore | Stratified random sampling | Mar 2015 – Feb 2016 | 24-h day | –32 % | Taylor et al. (2018a, 2018b) |
| Boat ramp | Stratification sampling schemes; (a) Random whole days | Oct 2014 – Sep 2015 | Varied (day and hour) | | Hamer et al. (2019) |

2. Materials and methods

#### 2.1. Study area

This study focused on digital camera data obtained at three boat ramps: Leeuwin and Hillaries in the West Coast Bioregion, and Denham in the Gascoyne Coast Bioregion (Fig. 1). Boating traffic at the three ramps selected generally reflects the varying magnitudes and different patterns of boating traffic at ramps in Western Australia (WA). Denham is a low use ramp, Leeuwin, a medium use ramp and Hillaries represents a high use ramp. The analysis of data from these ramps was also influenced by the need for ongoing recreational fishing surveys at these locations (Taylor et al., 2018b). In particular, the Leeuwin ramp was chosen because a complete 12-month camera record of powerboat retrievals exists (i.e., no outages) for the period in which the 2011–12 state-wide survey of boat-based fishing was conducted (Afrifa-Yamoah et al., 2020b; Ryan et al., 2013). Cameras have been positioned to ensure 100% coverage of boating traffic at each field of view and operate for 24 h daily. At Hillaries, information on boat movements is recorded when the boats pass a line between two fixed points adjacent to the boat ramp, whilst at Denham and Leeuwin the times at which boats return to the ramps are recorded (Bligh and Stuart, 2015). The type of vessel retrieved was recorded as either commercial, powerboat, jet-ski, kayak or other (e.g., government vessel). The current study focused on powerboats, being the most common vessel type used for boat-based recreational activity in WA.

#### 2.2. Data collection and treatment

The primary sampling unit in this study was calendar day. Camera data collected from three digital cameras were used (Fig. 1). Durations of camera footage analysed were 1 March 2011 to 29 February 2012 (a leap year) for the Leeuwin boat ramp, 1 May 2013 to 30 April 2014 for the Denham boat ramp and 1 September 2015 to 31 August 2016 (a leap year) for the Hillaries boat ramp. These time periods coincided with state-wide surveys of boat-based fishing (Ryan et al., 2013, 2015, 2017). All available camera data had previously been manually interpreted for the 12-month periods at each ramp. There were instances of missing data in the camera records for two ramps; 8% of all available minutes for Denham and 24% for Hillaries. Using climatic and temporal variables as covariates, missing observations were imputed using the methods described in Afrifa-Yamoah et al., 2020a. The counts of powerboat retrievals recorded from camera footage during these 12-month periods were used to assess bias, precision and accuracy in a sensitivity analysis.
2.3. Sampling units and monitoring design

For a finite population of size, we define $I = \{1, \ldots, N\}$ as the set of labels for the units in the population. The binary vector $s = (s_1, \ldots, s_N) \in \mathbb{Z} = \{0, 1\}^N$ such that

$$s_i = \begin{cases} 
1, & \text{if unit } i \text{ is in the sample} \\
0, & \text{if unit } i \text{ is not in the sample} 
\end{cases}$$

for all $i \in I$, then corresponds to a subset of selected samples from the population drawn without replacement. Then $\mathcal{S}_n = \left\{ s \in \mathbb{Z} \mid \sum_{i=1}^{N} s_i = n \right\}$.

Fig. 1. Study area showing the locations of the Hillarys (high-use), Leeuwin (medium-use) and Denham (low-use) boat ramps where remote camera data were recorded.
1 \leq n \leq N, \text{ denotes the set of all those vectors corresponding to samples of size } n. \text{ A sample design } p() \text{ thus is a function from support } \mathbb{S} \text{ to } [0, 1] \text{ such that } p(s) > 0 \text{ for all } s \in \mathbb{S} \text{ and } \sum_{k \in \mathbb{S}} p(s) = 1 \text{ (Berger and Tillé, 2009; Tillé, 2005).}

### 2.3.1. Design 1: Simple random sampling design (SRS)

For a fixed sample size, n, a standard draw-by-draw without replacement procedure was performed, where units in the population have equal probability of selection. Each sample unit has the probability \( \frac{n}{N} \) of selection. If the \( i^{th} \) unit is selected, it is removed from the population. The procedure is repeated n times, with the corresponding subset of powerboat retrievals, \( Y_i \), of the selected units (days) being used as the sample.

### 2.3.2. Design 2: Systematic sampling design (SSRS)

To select a fixed sample of size \( n \) from \( N \), we determined the quotient, \( k = \frac{N}{n} \). A random start, \( r \), was chosen between 1 and \( k \), and subsequently every \( k^{th} \) observation was selected until \( n \) samples were obtained. The serial numbers of the \( n \) samples would be \( r, r+k, r+2k, \ldots, r+(n-1)k \). It is important to note the systematic sampling design has a minimum support (Pea et al., 2007), which implies the cardinality of the sampling space is smaller than the population size and only the set of samples has positive probability of selection. Thus, selecting sample sizes of 0.5 or more of the population size would lead to repeated samples, which would not yield practical results in terms of assessing variability in jackknife resamples. As a result, this design was restricted to sample sizes of up to 0.4 of the population size.

Let \( Y_i \) denote the number of powerboat retrievals on day \( i \), then for a fixed \( n \) (that is, number of days sampled), the mean and associated variance of the number of powerboat retrievals for design 1 and 2 (with notations consistent with those used in Lohr, 2010) is given by

\[
\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} Y_i, \quad (1)
\]

\[
\hat{Var}(\hat{\mu}) = \left( \frac{1}{n-1} \right) \sum_{i=1}^{n} (Y_i - \hat{\mu})^2 \quad (2)
\]

The expansion estimators for the total number of powerboat retrievals and variability for designs 1 and 2 are obtained as follows;

\[
\hat{\text{Total}} = N\hat{\mu} \quad (3)
\]

\[
\hat{\text{Var}}(\text{Total}) = N^2 \left( 1 - \frac{n}{N} \right) \hat{\text{Var}}(\hat{\mu}) \quad (4)
\]

where \( 1 - \frac{n}{N} \) is a finite population correction factor, to correct the standard errors of the sample mean from samples obtained without replacement, especially for larger sample sizes to the population total, accounting for the loss in precision in the variance associated with the estimates (Lohr, 2010).

### 2.3.3. Stratified random sampling

The levels of powerboat retrieval counts are strongly influenced by seasonal and annual cycles (Desfosses and Beckley, 2015; Smallwood et al., 2012) and these temporal factors could influence the sampling process. In this study, the survey year was stratified into astral seasons (autumn, winter, spring, summer) and day-types (weekdays and weekend/public holidays), leading to eight post hoc strata (Table 2).

Let \( J \) be the number of strata, \( N_j, 1 \leq j \leq J \), the total number of units in stratum \( j \), and \( Y_{ij} \) the count of powerboat retrievals for unit \( i \) in stratum \( j \), then the estimate for the population average and associated variance are obtained by

\[
\hat{\mu} = \frac{1}{N} \sum_{j=1}^{J} N_j \hat{\mu}_j \quad (5)
\]

\[
\hat{\text{Var}}(\hat{\mu}) = \frac{1}{(N-1)^2} \sum_{j=1}^{J} N_j^2 \left( \frac{\sigma_j^2}{N_j} \right) \quad (6)
\]

where \( \hat{\mu}_j = \frac{1}{N_j} \sum_{i=1}^{N_j} Y_{ij} \), \( \sigma_j^2 = \frac{1}{N_j} \sum_{i=1}^{N_j} (Y_{ij} - \hat{\mu}_j)^2 \) and \( N_j \) is the number of samples selected from stratum \( j \).

### 2.3.3.1. Design 3: proportional allocation (SRSP).

In this sampling scheme the number of sampled units in each stratum is proportional to the size of the stratum, that is, the number of days in the stratum. For example, for a sample proportion of 0.1 in a stratified sampling design, a sample size proportional to 0.1 of the total sample size of the stratum will be drawn. The process is repeated for all strata and the sum of the sample sizes from the strata will amount to 0.1 of the population size, that is, 36 out of the number of days in the year that were available in the data. Within each stratum, simple random sampling without replacement was applied with a fixed sample size. The standard a draw-by-draw procedure where units in each stratum have equal probability of selection was performed. For a fixed sample size of \( n \) within stratum \( j \), the probability of selection is \( n_j = \frac{n}{N} \) for each unit in the stratum. The expansion estimators for the total number of powerboat retrievals and associated variability were obtained as follows;

\[
\hat{\text{Total}} = N\hat{\mu} \quad (7)
\]

\[
\hat{\text{Var}}(\text{Total}) = \left( 1 - \frac{n}{N} \right) \sum_{j=1}^{J} N_j^2 \hat{\text{Var}}(\hat{\mu}) \quad (8)
\]

### 2.3.3.2. Design 4: weighted allocation (SRSW).

In this study, the total number of powerboat retrievals was unequal across strata and provided useful information for defining the sampling weights, \( w_j \), for the strata. The weight, \( w_j \), of units sampled from each stratum was determined by the ratio of stratum total number of powerboat retrieval counts to the overall total. For each sampling proportion, sampling fractions within the strata were obtained by multiplying the sample size required to the ratio of stratum total number of powerboat retrieval counts to the overall total.

For each sampling proportion, sampling fractions within the strata were obtained by multiplying the sample size required to the ratio of stratum total number of powerboat retrieval counts to the overall total.

\[
\hat{\text{Total}} = \sum_{j=1}^{J} \sum_{i=1}^{N_j} w_j Y_{ij} \quad (9)
\]

\[
\hat{\text{Var}}(\text{Total}) = \sum_{j=1}^{J} (1 - w_j) N_j^2 w_j^2 \hat{\text{Var}}(\hat{\mu}) \quad (10)
\]

### 2.4. Data analysis

Jackknife resampling was carried out 10,000 times, where the number of days with associated counts of powerboat retrievals was drawn without replacement using the sampling techniques described. The sampling techniques were studied selecting sampling sizes of up to 90 % of the population size except for the systematic sampling design. For illustration, if the sampling effort was 20 %, then 73 days with associated counts of powerboat retrievals were selected based on the sampling designs, without replacement, for each run. For the days sampled, the associated counts of powerboat retrievals were used to obtain estimates of the average number of powerboat retrievals (\( \hat{\mu} \)), coefficient of variation (CV), root mean square error (RMSE) and coverage rate. The coverage rate measures the proportion of times that
the 95% confidence bounds for the estimates of the annual number of powerboat retrievals contain the true estimate for the ramps. For each jackknife draw, estimates of the average number of powerboat retrievals, the coefficient of variation (CV) and the root mean square error (RMSE) were calculated and coverage was assessed. In practice, a 90% confidence is often set as the minimum acceptable rate. Final estimates were averaged over the 10,000 jackknife sampled estimates. The bias, precision and accuracy were measured by the mean estimates, \( \bar{\mu} \), coefficient of variation, CV and root mean square error, RMSE respectively.

Relative standard error (RSE) was used to gauge how well the sample total measures up to the population total. In fisheries research practices, a relative standard error of 20% is often deemed an appropriate threshold (Vollstad et al., 2014). For each sampling design, the relative standard error was calculated as:

\[
RSE = \frac{\sqrt{\text{Var}(\text{Total})}}{\text{Total}} \times 100\% \tag{11}
\]

where \( \text{Total} \) and \( \text{Var}(\text{Total}) \) denote the expanded count and variance defined in Eqs. (9) and (10) respectively. The operating cost of camera data interpretation was obtained as the average reading cost per stratum summed across the strata

\[
Cost = R \times \sum_{j=1}^{\text{Total}} D_j \times T_{R_j} \tag{12}
\]

where \( D_j \) is the number of days and \( (T_{R_j}) \) the average reading time of 24-h camera footage in stratum \( j \) (Table 2) and \( R \) is the casual hourly pay rate (in Australian dollars).

All analyses were performed in R (version 3.6.2, R Core Team, 2019) using the ‘strata’ function in the ‘SamplingStrata’ package (version 1.5–1) (Barcaroli, 2014), ‘S.SY’ function in ‘TeachingSampling’ (version 4.0.1) (Rojas, 2020), and the ‘filter function in ‘dplyr’ (version 0.8.3) (Wickham et al., 2019).

### 3. Results

#### 3.1. Distribution of powerboat retrievals across ramps and strata

The distributions of powerboat retrievals differed with respect to the eight strata across the ramps (Table 2). More powerboat retrievals occurred in autumn and winter for the low traffic ramp (Denham). The daily average number of powerboat retrievals for weekends and weekdays in autumn and winter were similar for the low traffic ramp. In contrast, more powerboat retrievals occurred during summer at the moderate and high traffic ramps. The daily average number of powerboat retrievals recorded on weekends were more than on weekdays across the seasons for the moderate and high ramps.

#### 3.2. Estimation of the average number of daily powerboat retrievals

The designs provided estimates of the daily average number of powerboat retrievals, the coefficient of variation and root mean square error with one standard deviation error bars capturing the parameters for the ramps considered (Fig. 2). Estimates were similarly unbiased, precise and accurate across the various sampling proportions (Fig. 2). Uncertainty in the estimates of the daily average number of powerboat retrievals decreased with increased sampling proportion for all the designs. The level of uncertainty around the estimates associated with the performance measures varied among the sampling designs. There was lower accuracy and precision for the estimates obtained at lower sampling proportion for all the ramps considered.

#### 3.3. Estimation of the annual number of powerboat retrievals and cost

The estimated number of powerboat retrievals expanded to the entire year obtained from the sampling designs aligned with the known total counts of powerboat retrievals for all three ramps. Averages of expanded estimates for the 10,000 jackknife samples were unbiased and the uncertainty around the estimates declined with increased sampling proportion (Fig. 3). There were minor losses in accuracy for the systematic sampling designs (SSRS), however, it generally observed lower variability around its estimates. For the moderate and high traffic ramps, the cost associated with the stratified sampling design with weighted (SRSW) allocation was slightly higher than for the other designs. The

### Table 2

| Attribute | Stratum | Daytype | Season | Autumn | W/day | W/end | Spring | W/day | W/end | Summer | W/day | W/end | Winter | W/day | W/end | Total |
|-----------|---------|---------|--------|--------|-------|-------|--------|-------|-------|--------|-------|-------|--------|-------|-------|-------|
|           |         |         |        |        |       |       |        |       |       |        |       |       |        |       |       |       |
| Denham (Low traffic ramp) | | | | | | | | | | | | | | | | |
| Number of days in strata | 61 | 31 | 64 | 27 | 61 | 29 | 64 | 28 | 365 |
| Total number of powerboat retrievals | 1332 | 658 | 500 | 252 | 249 | 237 | 1220 | 610 | 5258 |
| Proportion of the overall total | 0.25 | 0.16 | 0.10 | 0.05 | 0.05 | 0.05 | 0.23 | 0.12 | 1 |
| Mean | 21.84 | 27.68 | 7.81 | 9.33 | 4.08 | 8.17 | 19.06 | 21.79 | 14.41 |
| Standard deviation | 19.45 | 20.15 | 8.42 | 8.93 | 4.15 | 6.13 | 13.75 | 15.13 | 15.23 |
| Average reading time for 24-hr footage (in hrs) | 1.18 | 1.53 | 1.88 | 1.94 | 2.17 | 3.23 | 0.98 | 1.25 | 1.23 |
| Leeuwin (Moderate traffic ramp) | | | | | | | | | | | | | | | | |
| Number of days in strata | 62 | 30 | 64 | 27 | 63 | 28 | 65 | 27 | 366 |
| Total number of powerboat retrievals | 1519 | 1887 | 894 | 1217 | 2206 | 2222 | 1210 | 1138 | 12,293 |
| Proportion of the overall total | 0.12 | 0.15 | 0.07 | 0.10 | 0.18 | 0.18 | 0.10 | 0.10 | 1 |
| Mean | 24.50 | 62.90 | 13.97 | 45.07 | 35.02 | 79.36 | 18.62 | 42.15 | 14.41 |
| Standard deviation | 19.45 | 20.15 | 8.42 | 8.93 | 4.15 | 6.13 | 13.75 | 15.13 | 15.23 |
| Average reading time for 24-hr footage (in hrs) | 2.51 | 3.68 | 3.11 | 4.58 | 3.20 | 4.60 | 2.25 | 2.82 | 2.82 |
| Hillarys (High traffic ramp) | | | | | | | | | | | | | | | | |
| Number of days in strata | 62 | 30 | 65 | 26 | 61 | 30 | 65 | 27 | 366 |
| Total number of powerboat retrievals | 3848 | 3255 | 5379 | 3115 | 6758 | 5169 | 1875 | 1254 | 30,653 |
| Proportion of the overall total | 0.13 | 0.11 | 0.18 | 0.10 | 0.22 | 0.17 | 0.06 | 0.04 | 1 |
| Mean | 62.06 | 108.50 | 82.75 | 119.81 | 110.79 | 172.30 | 28.85 | 46.44 | 83.75 |
| Standard deviation | 23.24 | 62.67 | 69.04 | 111.24 | 82.08 | 103.09 | 32.08 | 66.66 | 78.49 |
| Average reading time for 24-hr footage (in hrs) | 2.51 | 3.68 | 3.11 | 4.58 | 3.20 | 4.60 | 2.25 | 2.82 | 2.82 |
The cost of data interpretation was similar among all the designs for the low traffic ramp (Fig. 3).

### 3.4. Accuracy, precision and coverage rate estimates

The confidence bounds around the predicted margin of error estimates narrowed considerably from 0.4 sampled proportion for all the sampling designs, characterizing consistency and stability in the estimates obtained (Fig. 3). The RSE (± standard deviations) obtained by the sampling designs for sampling proportions from 0.4 and above were below the 20% threshold for three of the sampling designs across the three boat ramps (Table 3). For all the ramps, the RSE (± standard deviations) estimates were above the threshold prior to 0.4 sampling proportion for all the designs. The sampled totals obtained from the sampling designs for 0.4 sampled proportions and beyond aligned well to the observed totals. The relationship between the sampled proportion and RSE shows an exponential decay at increased sampling proportion. The level of precision improved as the sampling proportion increased. However, the rate of improvement decreased after 0.4 sampling proportion for all the designs. Also, the deviations around the relative standard error were generally narrowest for SRSW (Table 3).

The coverage rates observed for the sampling designs were within the acceptable range regardless of the sampling proportion. The designs achieved coverage of over 90% across the various sampling proportions, except for three instances (Table 3). The lowest coverage rate was 84% observed at 0.1 sampling proportion for SRSW observed at the low traffic ramp. SSS, except for the low traffic ramp, consistently obtained 95% confidence bounds that always contained the true estimate across the various sampling efforts. At 0.4 sampling proportion, SRSW achieved full coverage for the ramps. The differences in the coverage performance were more apparent for the data for the high traffic ramp. Although there was a logarithmic increase in coverage as the sampling proportion was increased for the various designs, the rate of increase was very slow for the stratified sampling with proportional allocation (SRSP) and the simple random sampling (SRS) designs (Table 3).

### 4. Discussion

This study provides a comprehensive a posteriori analysis to ultimately guide the design and resourcing of camera data sampling for recreational fishing surveys. The results demonstrate how the accuracy of estimates of the number of powerboat retrievals are influenced by the survey design and sampling proportion for low, moderate and high traffic-intensity boat ramps. Four classical random sampling designs were studied and the associated trade-offs were evaluated in terms of bias, accuracy, precision, coverage rate and cost using a jackknife resampling scheme. Unbiased estimates of the total number of powerboat retrievals were obtained and the underlying relationships for relevant performance measurement criteria for the sampling designs have been described. The reading of 40% of camera footage resulted in RSE values of 20% or less across the three boat ramps. Additionally, the absolute rate of change in the 95% predicted margin of error of the proportion of sampling effort on a continuous scale would be decreasing and flattening above a sampled proportion of 0.4 for the ramps. Therefore, manual interpretation of camera footage for 40% of the days within a year can be deemed as an adequate level of sampling effort to obtain unbiased, precise and accurate estimates to meet broad management objectives. Adoption of a policy of manual interpretation of 40% camera footage would considerably reduce the cost of data interpretation, since the operating cost increases linearly with increasing...
results were averaged over 10,000 resamples. The error bars are 1 standard error of the average of the estimates from the 10,000 resamples. The horizontal dashed lines represent the true point estimates based on a census of all counts from observed data sets. (SRS - simple random sampling, SSRS - systematic sampling, SRSP - stratified random sampling with proportional allocation, and SRSW - stratified random sampling with weighted allocation).

Table 3
Average relative standard error (± standard deviations) and the coverage rate from the 10,000 jackknife draws for the sampling designs across the sampling proportions from the camera records of Denham (low traffic), Leeuwin (moderate traffic) and Hillarys (high traffic) boat ramps (SRS - simple random sampling, SSRS - systematic sampling, SRSP - stratified random sampling with proportional allocation, and SRSW - stratified random sampling with weighted allocation).

| Ramp type | Sampling designs | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|-----------|------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Low traffic | SRS              | 34.04±8.29 | 24.09±6.31 | 19.69±5.29 | 17.05±2.78 | 15.25±2.10 | 13.98±1.78 | 12.92±1.02 | 12.10±0.98 | 11.42±0.76 |
|           | SSRS             | 33.96±3.69 | 24.12±3.12 | 20.28±2.59 | 16.77±1.62 | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  |
|           | SRSP             | 34.06±6.32 | 24.13±5.39 | 19.62±4.86 | 16.98±2.27 | 15.28±2.06 | 14.03±1.85 | 12.94±0.98 | 12.10±0.82 | 11.42±0.69 |
|           | SRSW             | 30.66±5.45 | 23.17±4.85 | 19.44±4.05 | 15.75±1.86 | 15.22±1.56 | 13.72±1.23 | 12.92±0.85 | 11.95±0.66 | 11.42±0.53 |
|           | SRS              | 26.58±7.68 | 17.66±6.89 | 13.48±6.05 | 10.80±5.38 | 8.81±4.56  | 7.26±3.89  | 5.77±2.08  | 4.43±1.68  | 2.97±1.02  |
| Moderate traffic | SRS              | 26.56±6.48 | 17.82±5.27 | 13.74±4.25 | 10.61±3.51 | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  |
|           | SSRS             | 25.60±7.06 | 17.88±6.56 | 13.41±5.98 | 10.78±5.02 | 8.82±3.58  | 7.28±3.09  | 5.79±2.33  | 4.41±1.97  | 3.64±1.23  |
|           | SRSP             | 26.97±5.23 | 18.51±4.26 | 15.08±3.39 | 11.70±3.03 | 9.17±2.41  | 7.76±2.01  | 6.79±1.27  | 5.49±0.92  | 2.97±0.65  |
|           | SRSW             | 22.16±6.25 | 19.11±5.95 | 14.61±5.03 | 11.71±4.79 | 9.55±4.09  | 7.87±3.98  | 6.25±3.06  | 4.80±2.98  | 3.22±2.35  |
|           | SRS              | 22.18±4.56 | 19.15±4.13 | 14.33±3.65 | 12.25±3.20 | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  |
| High traffic | SRS              | 22.68±5.68 | 19.20±5.08 | 14.61±4.95 | 11.71±4.23 | 9.56±3.99  | 7.88±3.78  | 6.25±3.25  | 4.80±2.78  | 3.22±2.26  |
|           | SSRS             | 21.76±5.09 | 18.76±4.62 | 14.53±4.25 | 10.87±4.01 | 9.51±3.75  | 7.52±3.06  | 6.44±2.52  | 4.76±2.34  | 3.23±1.79  |
|           | SRSP             | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  |
|           | SRSW             | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  | – – – – –  |

Note: Results in italics indicate that the point RSE estimates were above the 20 % threshold (Volstad et al., 2014).
sampling proportion. It could serve as a useful reference to guide recreational fishing survey practitioners in determining the adequate levels of sampling effort for interpreting data from digital camera monitoring to estimate fishing effort and catches.

By construction, the four classical sampling designs considered in this study could be divided into two groups: the non-stratified group and stratified group. The non-stratified group included the simple random sampling (SRS) and the systematic sampling (SSRS); and the stratified group included the stratified sampling designs with proportional (SRSP) and weighted allocation (SRSW). On average, the estimates obtained from the samples selected by the designs in the 10,000 jackknife draws were unbiased, and accurate with varying variability across sampling proportion, and notably less precise at low sampling fractions (high RSEs). The non-stratified group behaved differently in terms of the variability around their estimates. SRS most often obtained estimates with large variability compared to SSRS. Stratified designs yielded more consistent estimates with their variability decreasing in a well-defined fashion across sampling proportion. Based on the behaviour of the coefficient of variation, SRSP was more consistent in estimating sample variability comparable to population estimates for low and moderate traffic ramps. However, SRSW was more consistent for the high traffic proportion, and notably less precise at low sampling proportion. SRSW was generally more accurate but the most expensive (Fig. 3).

Classical sampling designs considered in this study are simple to understand and easy to implement in recreational fishing surveys (Table 1) and other studies. Simple random sampling, stratified random sampling, systematic sampling and stratified systematic unaligned sampling schemes have been studied as suitable sampling designs for classified digital sensing data (Hashemian et al., 2004). In the present study, SRS was the worst performing design as measured by the coverage, implying that it was the least stable design in the jackknife draws performed. Although the sampling units have equal probability of selection, the design is prone to yielding samples that are not representative of the population and at smaller sampling proportion, resulting in more variability among the sample estimates (Lohr, 2010). However, it provided unbiased average estimates of the total number of powerboat retrievals with varying variability (often comparatively larger to the other designs) across the various sampling effort for the ramps considered.

The systematic random sampling (SSRS) is a good proxy for the simple random sampling (SRS). It is very simple in execution relying on a sampling interval to select sampling units and gives better coverage of the population space. It always performs better than the simple random sampling for a well-defined population that exhibits no patterns and has low risk of manipulation (Lohr, 2010). From the results obtained, SSRS presents as a useful sampling design and would yield sample estimates that are unbiased, accurate and precise, especially in instances where there is no prior knowledge of strata level and the data do not have any cyclical patterns. The design should, however, be used with caution especially in deciding on the sampling interval to be used. For instance, boating traffic is influenced by whether the day is a weekend or weekday (Deslosses and Beckley, 2015); in effect, more boating activities are often recorded on weekends than on weekdays. For some sampling intervals, SSRS could contain either all weekends or all weekday, thereby losing its representativeness and provide biased estimates of the population parameters. In addition, the design has low entropy, implying that the distribution of the probability mass function of this design is weakly spread, which is smaller than the population size (Pea et al., 2007).

The stratified sampling design with proportional allocation (SRSP) obtained samples that were miniature versions of the population (Lohr, 2010), promoting long term usage of sampled data obtained from this design in time series studies for trend detection and other comparisons. This design is weighted under stratified simple random sampling if the cost of data collection and variability is uniform across strata. Otherwise, weighted allocation (SRSW) provides the best estimates. In this study, SRSW was not the most cost-efficient design because the criterion used for determining sample size within strata did not consider cost. More samples were drawn from busy strata which had higher associated reading cost associated because readers required more time to interpret data compared to less busy strata for the same duration of footage. In effect, more cost was incurred as the sampling intensities were higher in busier strata. The high coverage rates achieved by the designs with stratification component in estimating total recreational boating effort at various sampling proportion are encouraging, implying they would fit in well with camera surveys which mostly incorporate the stratified random sampling design (Table 1) as well as other on-site surveys, for example, the bus-route method in Lai et al. (2019). This study highlights that it would be beneficial for researchers to consider reading a full year of data to provide suitable weights for on-going low-level monitoring. It is suggested that a census of boating effort must be repeated at regular intervals to guard against potential unusual boat behaviour and to detect emerging trends. Generally, the number of strata is chosen in a fashion that minimizes the variance of the estimator of the population total, which is followed by the optimal allocation of samples within strata. According to Schoaffer et al. (2006), the three factors that determine the best allocation for each stratum are the total number of elements, the associated variability of observations in each stratum and the cost of obtaining an observation from each stratum.

The level of resolution of the primary sampling unit used in this study adds to the simplicity of application of the sampling designs in practice. In a trial study, Hamer et al. (2019) used randomly sampled hourly blocks within days of boat launching and retrieval activities and then used a model-based estimator to predict effort occurring at other times. Their preliminary results achieved greater than 80 % accuracy when 30 % of available images were used, suggesting that their method has potential in the estimation of effort and catch. However, in Western Australia, recreational fishing activities are dynamic within the day, distributions of activities across hours of the day differ significantly and estimates based on hourly blocks sampled would greatly affect the estimates obtained from a model-based estimator (Lai et al., 2019; Ryan et al., 2017). Overcoming the modelling complexity would require that more assumptions must be made, which would compromise the estimates obtained. Adopting different weighting schemes for type of days and daily hourly intensities of boating activities across sampling strata could overly complicate the model, and would not ultimately resolve the fact that the estimation process could lead to biased estimates (Gelman, 2007). We anticipate that modelling the daily distributions within strata would compare much better in precision and accuracy of estimates than modelling the distributions of daily hourly blocks.

Hartill et al. (2019) highlighted the need to optimize the utility and value of information provided by digital camera monitoring, more importantly in the area of reading cost. The decision to determine an optimal level of days of camera footage to be interpreted is a subjective call and would be driven by several factors including survey objectives. For example, when digital camera data are used to validate estimates of fishing effort from other surveys (with adjustment for non-fishing activities) a larger sampling fraction, or even a census of footage, may be considered an appropriate level of footage to manually interpret. In surveys that involve concurrent digital camera and on-site surveys, gains in precision and accuracy of the estimated number of powerboat retrievals flow through to estimates of fishing effort and catch (Steffe et al., 2008, 2017; Taylor et al., 2018b). In this instance, the survey practitioners also wish to validate a high fraction of activity. Alternatively, when the number of powerboat retrievals is used as a proxy for fishing effort between surveys (i.e. low-level monitoring), a lower sampling fraction may be considered appropriate. Therefore, the manual reading of 40 % of sampling days is unlikely be optimal for all digital camera datasets. Another issue of concern is dealing with missing data. Analytical techniques have been developed to impute for missing periods (Afriya-Yamoah et al., 2020b; Hartill et al., 2016; van Poorten et al., 2015). However, if the proportion of missing data is relatively
small and it is reasonable to assume that data are missing at random, then such days could be removed from the sample (Smallwood et al., 2012; Taylor et al., 2018a).

5. Conclusion

While the automation of the monitoring system would ultimately provide a cost-efficient means of data interpretation (Buch et al., 2011), advances in this technology are in an early phase in monitoring recreational fishing effort (Hartill et al., 2019). Thus, in the interim and beyond, this study would improve the utility of digital camera monitoring by reducing the cost of manual data interpretation and data storage. The consistency in the trends of the relationships between the performance indicators, cost across ramps and sampling proportion from the sampling designs are indicative of the significant gains achieved and their reliability in practice. The re-sampling approaches applied in this study would be relevant to other types of recreational fishing surveys (e.g., boat ramp surveys) and are also broadly applicable to other areas of fisheries research where decisions on sampling intensity need to be considered alongside cost and data quality. This will guide recreational fisheries researchers to evaluate expected precision in relation to sampling proportion in their management domains.

CRediT authorship contribution statement

Ebeneezer Afrifa-Yamoah: Conceptualization, Formal analysis, Visualization, Methodology. Stephen M. Taylor: Project administration, Writing - review & editing. Ute Mueller: Funding acquisition, Project administration, Writing - review & editing.

Declaration of Competing Interest

None.

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