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Marine Mammal Survey and Assessment Methods

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In Memoriam: Dr Gerald W. Garner, 1944 – 1998

Dr Gerald W. Garner examines a darted polar bear before attaching a radio-transmitter, on the sea ice of the Chukchi Sea. (Photo courtesy S. Schliebe.)

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Modeling variability in replicated surveys at aggregation sites

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ABSTRACT: Surveys of aggregation sites can provide unbiased estimates of annual trends in population size if the proportion of the population counted at these sites does not vary systematically among years. However, counts at these sites tend to be highly variable and resulting trend estimates typically have poor precision. I developed an index based on a simple parametric model for counts of Pacific walruses (*Odobenus rosmarus divergens*) at haul-out sites in Bristol Bay, Alaska that accounted for the general temporal pattern of variability in the proportion of the population at the sites. Simulations suggested that an index based on mean annual counts was a more sensitive indicator of trend than the model-based index or the currently used index based on maximum annual counts. The model-based index may be more useful for other situations where timing of the aggregation peak is more variable.

Keywords: adjusted count, aggregation, availability bias, haul-out, model, monitor, *Odobenus rosmarus*, power, survey, time series, trend, walrus

1 INTRODUCTION

Many wildlife species form large aggregations at predictable locations in time and space and counts of individuals at these sites have often been used as a basis for monitoring populations. For example, various species of birds have been monitored at sites where they aggregate in winter (Eggeman & Johnson 1989) or during migration (Titus & Fuller 1990, Pyle et al. 1994). Brown bears have been monitored along streams where they aggregate to feed on spawning salmon (Barnes et al. 1995). Manatees have been monitored at warm-water springs and discharge sites where they aggregate in winter (Garrott et al. 1994). Pinniped populations have been monitored where they aggregate at haul-out or breeding areas (Eberhardt et al. 1979, Thompson & Harwood 1990). Aggregation sites offer the opportunity to observe potentially large portions of populations that might not be easily detected elsewhere because of low density, inaccessibility, or low detectability (Hussell 1981). However, the utility of counts from these sites is limited because they do not comprise a probability-based sample (Eggeman et al. 1997). Also, the proportion of the population that is at these sites during any given survey can be highly variable and is usually unknown (Eberhardt et al. 1979, Mansfield & St. Aubin 1991).

Surveys of aggregation sites can provide unbiased estimates of annual trends in population size if the proportion of the population counted at these sites does not vary systematically among years (Hussell 1981, Titus & Fuller 1990, Pyle et al. 1994). However, even in the absence of systematic variation in this proportion, random variation can be high and resulting trend estimates typically have poor precision. In some cases, it may be possible to identify factors affecting the proportion counted and then adjust counts for these factors by modeling them as covariates (Hussell 1981, Myers & Bowen 1989, Thompson & Harwood 1990, Garrott et al. 1994, Pyle et al. 1994, Dunn et al. 1997). Adjusted counts can provide the basis for an index that is less subject to variation in the proportion counted and is, therefore, a more sensitive indicator of population trend. This paper reports on an initial attempt to develop a simple model that accounts for some of the variation in the proportion counted and to use the model to improve trend estimates and evaluate monitoring designs for Pacific walruses (*Odobenus rosmarus divergens*) at haul-out sites in Bristol Bay, Alaska.

The summer population of Pacific walruses in Bristol Bay has been monitored with daily counts at terrestrial haul-out sites where the animals aggregate (Wilson 1996). Most of the walrus population that winters in this region migrates north with the ice pack in spring (Fay 1982). However, thousands of mature males along with a few females and young remain in Bristol Bay where they use several traditional haul-out sites throughout summer and fall (Fay 1982). Walruses usually begin appearing at these haul-outs in May or June, reach peak numbers from July through September, and continue to use them through, at least, November (Fay 1982, Hills 1992). Individual walruses may follow patterns ranging up to 7-10 days at sea followed by 2-4 days at a haulout or they may make daily trips to sea and back from a haulout (Hills 1992). A single walrus may follow each of these patterns at different times. Movements of walruses on and off a haul-out may be synchronized to some extent (Taggart 1987).

Counts of walruses at a haul-out site are highly variable, with numbers tending to build and then decline over periods of several days, forming a series of more or less distinct peaks during a season (Taggart 1987, Mansfield & St. Aubin 1991). Some of the variability in daily counts may be attributable to environmental factors. Factors related to disturbance (by humans or polar bears), weather, tidal state, and time-of-day can affect haul-out behavior of walruses (Fay & Ray 1968, Salter 1979, Mansfield & St. Aubin 1991, Hills 1992) and other pinnipeds (Bartholomew & Wilke 1956, Ray & Smith 1968, Ling et al. 1974, Schneider & Payne 1983). However, attempts to model counts of walruses at haul-outs as functions of these factors have explained only a small amount of total variation in counts (Salter 1979, Hills 1992).

Annual trends in counts of walruses at Bristol Bay haul-out sites have been assessed primarily with informal comparisons of maximum daily counts from each year (Wilson 1996, Fay et al. 1997). Alternative indices of population size and alternative monitoring designs have not been investigated. I considered daily count data from selected years and from a subset of the principal haul-out sites in Bristol Bay. My first objective was to develop a simple parametric model of the counts that reflected the general temporal pattern of variability in the proportion of the population at the sites but did not make any direct reference to environmental covariates. Changes in parameters of this model would correspond to changes in the pattern of variability. Given such a model, my second objective was to use the model to develop an index that would be less affected by changes in the pattern of variability. If the model adequately represented the pattern of variability and annual differences in this pattern were of sufficient magnitude, this index would be expected to provide a more sensitive estimate of trend than indices based on unadjusted counts. My final objective was to use the model as a basis for simulation to evaluate power for detecting trend with the model-based index versus more traditional design-based indices under a range of potential monitoring designs.

2 METHODS

2.1 *Survey methods and data selection*

Cape Pierce and Round Island are the 2 principal haul-out areas used by walruses in Bristol Bay, Alaska (Wilson 1996). Each of these areas contains several disjunct beaches where walruses haul out. Cape Pierce has the advantage that traditional haul-out beaches are readily accessible and can be surveyed regardless of weather conditions. Togiak National Wildlife Refuge has maintained a seasonal field camp at Cape Pierce from about mid-April or May through September each year since 1985. Refuge personnel stationed at the camp have attempted to make daily counts of walruses on all haul-out beaches. Methods have varied slightly from year to year, but in general, counting began between 0830 and 1030 each morning. Observers walked to specified viewing locations at each beach and used binoculars to count any walruses present. Counts included walruses hauled out on land as well as walruses in water near the haul-out. Multiple counts were usually made at each beach; extreme counts (e.g., counts that differed from the others by > 5% if there were 3 counts, or highest and lowest if there were ≥ 4 counts) were discarded and remaining counts averaged.

I treated the complex of haul-outs at Cape Pierce as a single site and considered combined totals of the averaged daily counts from all haul-outs. I examined plots of these daily totals for 1986 through 1991 field seasons. I selected for further consideration the 3 years (1986, 1989, and 1991) that appeared to have relatively continuous coverage from when walruses first began appearing at haul-outs until the start of the period when haul-out use declined (Mazzone 1986, Jemison 1989, Jemison 1992). For each of these years, I used all daily totals, beginning with the first non-zero total after relatively continuous coverage began.

2.2 *Temporal availability model*

For any given haul-out (or set of haul-outs), we can define a population of walruses comprised of all those individuals that use the haul-out at least once during a given year. The expected number of individuals that will be hauled out at that site during the count at time t in year i is given by $E(Y_{it}) = N_i A_{it}$, where N_i is the number of individuals that comprise the population using the site in year i and A_{it} is the probability that an individual from the population in year i will be on the haul-out at time t.

I refer to A_{it} as the availability function. It gives the expected proportion of the population hauled out at the site at any given time. We cannot directly estimate the availability function from count data alone. However, if counts are proportional to the availability function, we can use count data to estimate a rate function (Garrott et al. 1994) that will be proportional to the availability function. If R_{it} is a rate function proportional to A_{it}, then $E(Y_{it}) = \eta_i R_{it}$, where η_i is proportional to N_i and is the expected value of the adjusted counts Y_{it} / R_{it}. If differences in availability account for a sufficient portion of the variance in counts, the estimate of η_i will be less variable than unadjusted counts and therefore more sensitive to changes in population size.

For the purpose of modeling haul-out data, I factored availability into 2 components. Let $A_{it} = P_{1it} (P_{2it} \mid P_{1it})$, where P_{1it} is the probability that a walrus in the population has moved into Bristol Bay and begun using haul-outs by time t and $P_{2it} \mid P_{1it}$ is the conditional probability that a walrus will be on a Cape Pierce haul-out at time t, given that it has moved into Bristol Bay and begun using haul-outs. The pattern represented by P_{1it} is one of increasing availability as walruses begin moving into the bay and using haul-outs in May and June, reaching a maximum during the July-September period and then decreasing as walruses begin to leave in November. One of the simplest functions that follow this general pattern is a quadratic. I let the rate function corresponding to P_{1it} be $R_{1it} = \exp(-b_i (c_i - t)^2)$ which is the exponential of a quadratic function that attains its maximum value (if $b_i > 0$) at time $t = c_i$. In this formulation, b_i is a scale parameter that controls how quickly the maximum value is reached. Both b_i and c_i are unknown parameters that must be estimated.

$P_{2it} \mid P_{1it}$ represents movements on and off Cape Pierce by walruses that are in the area and using haul-outs. Without any data other than counts, I treated these movements as essentially random, with a correlation structure that represented the degree of synchrony. I let the rate function corresponding to $P_{2it} \mid P_{1it}$ be

$$R_{2it} = \exp\left(\sum_{j=1}^{n} d_{ij} \ln(Y_{i,t-j}) \right) \tag{1}$$

which is an exponential of an order-n autoregressive function of the log-counts (Chatfield 1982). The number of terms (n) in the autoregressive function and the regression coefficients (d_{ij}) are all unknowns that must be estimated. Putting the pieces together and taking logarithms gives

$$E(\ln(Y_{it})) = a_i - b_i(c_i - t)^2 + \sum_{j=1}^{n} d_{ij} \ln(Y_{i,t-j}) \tag{2}$$

where $a_i = \ln(\eta_i)$ is the maximum of the expected log-counts adjusted for the portion of the movement on and off the haul-out that can be explained by autoregressive terms. More precisely, a_i is the maximum value that can be attained by

$$E(\ln(Y_{it})) - \sum_{j=1}^{n} d_{ij} \ln(Y_{i,t-j}) \tag{3}$$

and it represents the maximum of the underlying curve describing population movements into and out of Bristol Bay. The estimate of a_i can serve as an index to population size. Model (2) is nonlinear in parameters b_i and c_i, but it can be reparameterized to give

$$E(\ln(Y_{it})) = \alpha_i + \beta_i t + \gamma_i t^2 + \sum_{j=1}^{n} d_{ij} \ln(Y_{i,t-j}) \tag{4}$$

which is a standard, linear, autoregressive model of order n with quadratic trend that can be fit using standard regression software. After fitting (4), we can estimate the parameters in (2) as

$$\hat{a}_i = \hat{\alpha}_i - \frac{\hat{\beta}_i^2}{4\hat{\gamma}_i} \tag{5}$$

$$\hat{b}_i = -\hat{\gamma}_i \tag{6}$$

and

$$\hat{c}_i = \frac{-\hat{\beta}_i}{2\hat{\gamma}_i} \tag{7}$$

In the usual case where covariates are used to adjust counts (Hussell 1981, Garrott et al. 1994), values of covariates change but the relation between counts and covariates is assumed to remain constant over time. Adjustments to counts remove variation due to annual differences in values of covariates by standardizing counts to a given value (usually the mean) of the covariates. In model (2), the covariate is time within year. There are essentially no annual differences in values of this covariate because counts are made every day over essentially the same time period each year. However, the pattern of availability over this time period may vary from year to year. For example, date of maximum availability or rate of increase to maximum availability may change from year to year, possibly due to variability in environmental factors. In the context of model (2), these types of changes would be reflected in changes to parameters b_i and c_i. If estimates of parameters are allowed to vary among years, adjusted counts can account for differences in parameters as well as covariates. The index $\hat{a}_i$ can be thought of as the log-count, adjusted for annual differences in time of maximum availability and synchrony in movements on and off haul-outs.

2.3 *Model fitting and simulation*

Counts were transformed by adding 1 and taking logarithms. Model (4) was fit to the transformed counts for each year separately, starting without any autoregressive terms. Autoregressive terms were then successively added if the partial F-test for their addition was significant ($\alpha = 0.05$) and Akaike's information criteria (AIC) was reduced (Chatfield 1982). After fitting all autoregressive terms, the quadratic term was removed if its partial F-test was not significant ($\alpha = 0.05$) and its removal decreased AIC. Parameter estimates for model (2) were obtained from (5), (6), and (7). Standard errors for parameter estimates in (2) were obtained by refitting models with nonlinear regression and inverting the information matrix. Parameter estimates in (2) could also have been obtained directly with nonlinear regression.

Data were simulated with model (2) for power analysis. The number of autoregressive terms was the maximum used in any of the final models for 1986, 1989, and 1991 data. Parameters b_i and c_i were generated independently for each year as bivariate normal random variables. Autoregressive parameters d_{ij}, $i = 1, \cdots, n$ were generated independently for each year as multivariate normal random variables (with bounds of $-1 < d_{ij} < 0$, or $0 < d_{ij} < 1$, depending on whether $\hat{d}_{ij} < 0$ or $\hat{d}_{ij} > 0$). The pair of parameters b_i and c_i was assumed to be independent of the set of parameters d_{ij}, $i = 1, \cdots, n$. Means, variances, and correlations of random parameters were taken to be the mean, variance and correlation of corresponding parameter estimates from 1986, 1989 and 1991. Error variance was taken to be the mean of error variance estimates from 1986, 1989 and 1991.

The parameter a_i was allowed to vary systematically over time to represent an exponential annual decrease in size of the population using haul-outs. Thus, $a_i = a_0 + (i - 1)\ln(1 - r)$, where a_0 was the mean of a_i estimates from 1986, 1989 and 1991 data and r was the exponential rate of decrease on the scale of original counts. Separate sets of simulations were conducted for values of $r = 0.02$, 0.04, 0.06, 0.08, and 0.10.

In each simulation, data were generated to represent a 10-year monitoring period with daily counts during the monitoring period each year. Separate sets of simulations were conducted for a 134-day period (corresponding to mean start and end dates for 1986, 1989, and 1991 monitoring data), and 61-, 31- and 15-day periods each centered on $E(c_i)$, the expected day of the maximum count.

For each year of a 10-year simulation, I obtained the maximum log-count ($\hat{m}_i$), the mean log-count ($\hat{u}_i$) and $\hat{a}_i$; $\hat{m}_i$ and $\hat{u}_i$ are unadjusted, design-based indices of population size. $\hat{a}_i$ is an adjusted index based on model (2). P-values for partial F-tests of slope coefficients were obtained from linear regressions of each index on year. Each simulation was repeated 1000 times. Power to detect trend at a given level of α was estimated as the proportion of 1000 simulations with $P \leq \alpha$.

Additional sets of simulations were conducted with data generated as described above except that variances of random parameters were increased. Separate sets of simulations were conducted with variances of all random parameters multiplied by factors of 2, 4, and 6.

When data are generated according to model (2) with random parameters, the resulting counts can be negative. The probability of negative counts increases with variance of the random parameters. Therefore, simulations were repeated with data generated by a more realistic version of model (2) in which any generated counts that were < 0 were reset to 0.

3 RESULTS

3.1 *Model fitting*

The model selection procedure resulted in second order, autoregressive models with quadratic trend for all 3 years (Table 1). Models appeared to fit reasonably well (Figure 1) and explain a substantial portion of variation in counts ($R^2 \geq 0.74$, Table 1). Parameter estimates for the first autoregressive term were slightly greater than 1 in 1986 and 1991. This suggests that these series may not be stationary. Nonstationarity may be a result of quadratic terms not fully accounting for underlying trend, or a changing correlation structure (amount of synchrony in movements) over the monitoring period within these years.

3.2 *Simulation*

When data were generated according to model (2) with parameter variances as estimated from 1986, 1989 and 1991 data (Table 1), power for $\hat{m}_i$ was about the same as for $\hat{a}_i$ and both of these were less than power for $\hat{u}_i$ (Figure 2). However, power for $\hat{a}_i$ was only slightly reduced by increasing parameter variances. Power was greatly reduced for both $\hat{m}_i$ and $\hat{u}_i$, as parameter variance increased. Performance of $\hat{a}_i$ became superior to that of $\hat{m}_i$ when variances were multiplied by 2 and superior to that of $\hat{u}_i$ when variances were multiplied by 4. Performance of $\hat{u}_i$ was superior to that of $\hat{m}_i$ at all levels of parameter variance.

When data were generated according to (2) with counts bounded at 0, power for $\hat{u}_i$ and $\hat{m}_i$ remained about the same as when counts were not bounded (Figure 3). However, when counts were bounded, the model used to obtain $\hat{a}_i$ did not fit as well and power was reduced. In this case, power for $\hat{a}_i$ was also greatly reduced by increasing parameter variances and $\hat{u}_i$ had superior performance over the full range of variances I considered.

Reductions in the monitoring period were critical to performance of the model-based index $\hat{a}_i$ because shorter periods did not contain enough curvature to fit a quadratic model. Reduction of period length had much less effect on design-based indices. Performance of $\hat{u}_i$ was almost the same for a 61-day period as for a 134-day period (Figure 4), but further reductions resulted in more substantial losses of power.

Table 1. Annual estimates of parameters in model (2) for Cape Pierce haul-out data and mean values used for simulating haul-out counts.

Parameter	Estimate (SE) 1986	1989	1991	Mean (SD)[a]
a_i	2.81 (0.46)	2.12 (0.53)	3.00 (0.44)	2.64 (0.46)
b_i	0.00027 (0.00013)	0.00020 (0.00007)	0.00024 (0.00007)	0.00023 (0.00003)
c_i	246.29 (12.01)	236.37 (10.95)	235.42 (10.04)	239.36 (6.02)
d_{i1}	1.10 (0.08)	0.75 (0.09)	1.02 (0.08)	0.96 (0.18)
d_{i2}	-0.49 (0.08)	-0.11 (0.10)	-0.46 (0.08)	-0.36 (0.21)
σ^2	1.86	1.09	0.85	1.26
R^2	0.74	0.78	0.82	

[a]SD of the 3 annual estimates. Correlations of the 3 annual estimates were 0.80 for a_i and b_i, and -0.99 for d_{i1} and d_{i2}.

Power to detect a 10% annual increase with $\hat{u}_i$ was quite high (e.g., power = 0.96 for 134-day period at $\alpha = 0.05$), but that corresponds to a rather large population decrease of 61% (on the original scale of counts) over the 10-year period. Power decreased rather quickly as the size of annual population change decreased (Figure 5). Power to detect a 5% annual decrease (corresponding to a 37% decrease over 10 years, on the original scale of counts) was only 0.42 for a 134-day annual monitoring period at $\alpha = 0.05$.

4 DISCUSSION

If parameter values in model (2) are fixed and there is no random variation, maximum and mean counts over any given set of dates will be linear functions of a_i. With the addition of random error, $\hat{a}_i$ becomes an unbiased estimate of a_i while $\hat{u}_i$ and $\hat{m}_i$ become unbiased estimates of linear functions of a_i. However, coefficients of variation for $\hat{u}_i$ and $\hat{m}_i$ are much smaller than the coefficient of variation for $\hat{a}_i$. Thus, for a fixed set of dates and parameter values, design-based indices $\hat{u}_i$ and $\hat{m}_i$ are better than the model-based index $\hat{a}_i$ at tracking annual changes in a_i. Simulations demonstrated that these relations continue to hold even when parameters are not fixed, unless annual variation in parameter values is quite large. Parameter variances had to be increased 2 to 4-fold before $\hat{a}_i$ began to outperform $\hat{u}_i$. Furthermore, performance of $\hat{a}_i$ was not robust to the form of the model generating counts.

For the most realistic model, which did not allow negative counts, and for parameter variances estimated from 1986, 1989 and 1991 data, $\hat{u}_i$ always outperformed the other indices. $\hat{u}_i$ also appeared to be relatively robust because its performance was not affected by using a less realistic model that allowed negative counts. Simulations suggested that monitoring period length could be substantially reduced without affecting power to detect trends with $\hat{u}_i$. However, the simulations also suggested that power to detect trends with $\hat{u}_i$ would be relatively high (e.g., ≥ 0.80 at $\alpha = 0.05$) only if the trends represented relatively large changes in population size (e.g., $r \geq .08$ for ≥ 10 years).

Results from simulations presented here should be considered cautiously. The simulations clearly showed that power for detecting trends with any of the indices depended on magnitude of annual variation in model parameters. The variance estimates I used were conservative in the sense that they included variation due to estimating parameters as well as annual variation in parameter values. However, estimated variances were based on data from only 3 selected years that may not represent the full extent of parameter variation. Therefore, results presented here are intended to be primarily illustrative of the approach.

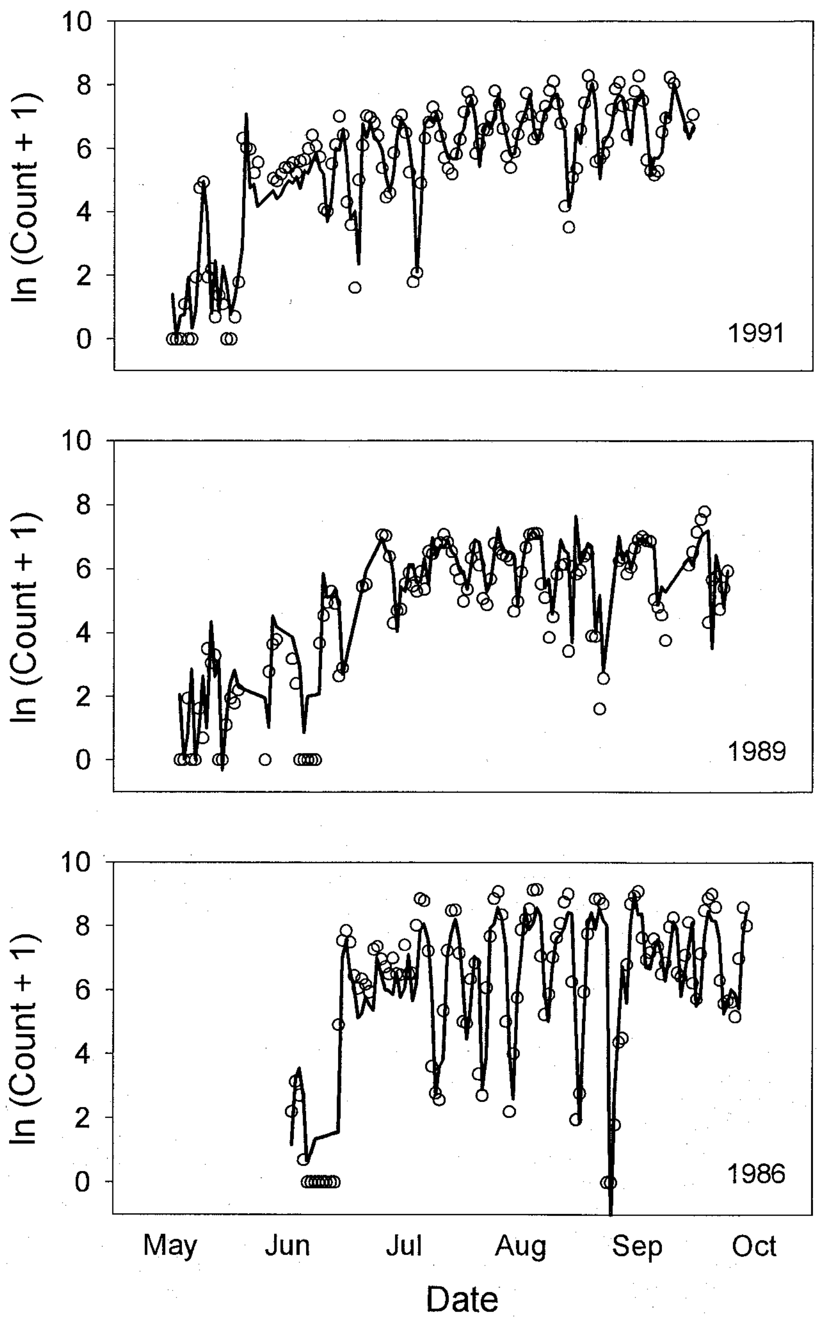

Figure 1. Fitted values (lines) for daily counts (circles) of walruses at haul-outs on Cape Pierce, Alaska, 1986, 1989 and 1991.

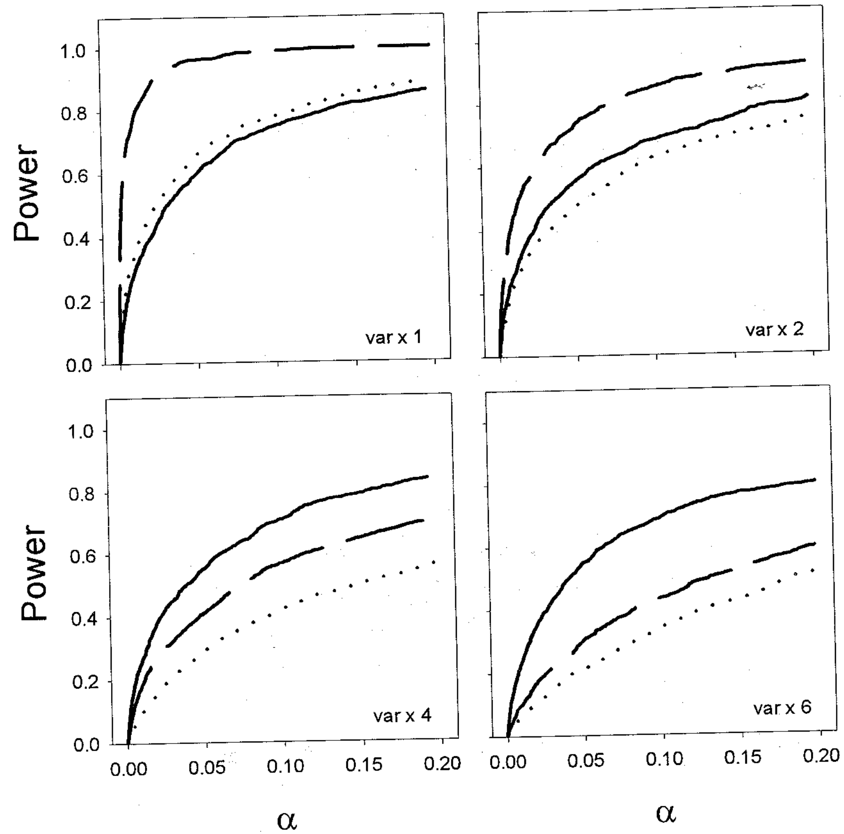

Figure 2. Power as a function of α-level for tests of trend based on $\hat{a}_i$ (solid lines), $\hat{m}_i$ (dotted lines) and $\hat{u}_i$ (dashed lines). Data were generated with model (2) assuming a 134- day annual monitoring period, a decreasing trend of 10% per year (r = 0.10) for 10 years, and parameter variances that ranged from 1 to 6 times the estimated variances.

Final conclusions should not be made until all historical data for Cape Pierce haul-outs are assembled and analyzed. However, preliminary results suggest that, of the indices I considered, mean annual counts may be the most sensitive and robust for monitoring walrus haul-outs. Also, it appears that it will be useful to focus future efforts on monitoring design refinements. It may still be possible to develop a more sensitive index by also adjusting for environmental covariates. An index such as $\hat{a}_i$ that adjusts only for temporal pattern may be useful for situations where timing of the aggregation peak is more variable relative to timing of surveys.

In the context of simulation, it was convenient to test for trend by independently estimating indices for each year and then regressing the indices against year. More powerful tests for linear trends could be obtained by fitting data for all years to a single model representing $\hat{a}_i$ or $\hat{u}_i$, as a linear function of year. For $\hat{a}_i$, this approach would require nonlinear regression. For $\hat{u}_i$, this approach would require autoregressive or other time-series models to account for correlation in daily counts.

For the work reported here, I assumed that errors in counts of walruses at haul-outs were small compared to other sources of variation, so counts could be treated as if they were exact. However, thousands of walruses can be found at a single haul-out and they typically huddle so closely that their bodies overlap (Fay & Ray 1968), making them extremely difficult to accurately count. Additional research will be required to assess the variability and potential biases associated with errors in counts.

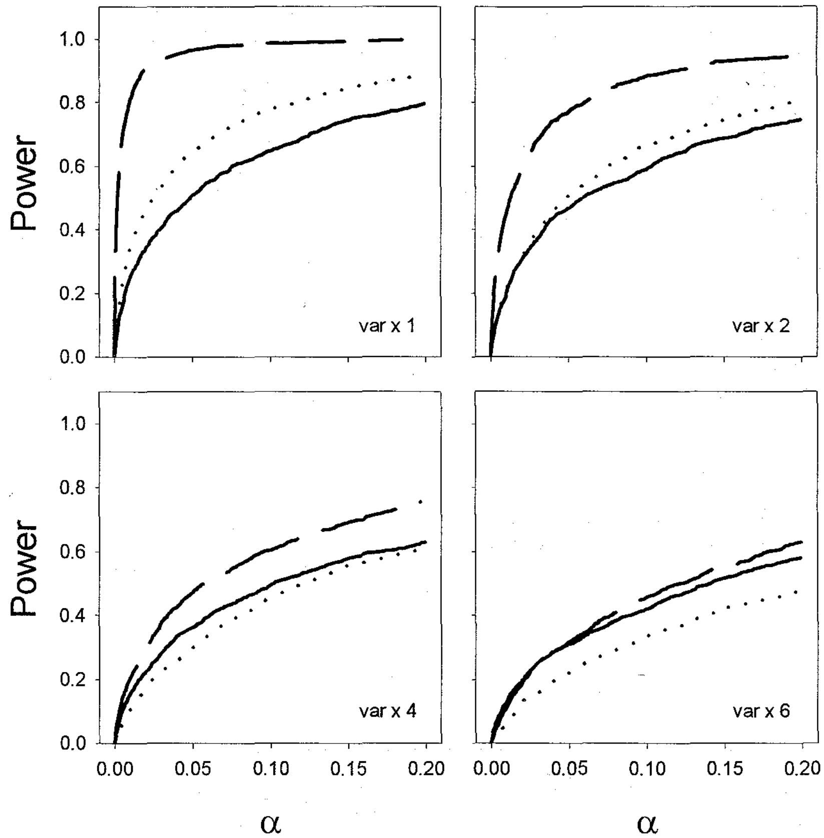

Figure 3. Power as a function of α-level for tests of trend based on $\hat{a}_i$ (solid lines), $\hat{m}_i$ (dotted lines) and $\hat{u}_i$ (dashed lines). Data were generated with a more realistic version of model (2) that did not allow negative counts. The model assumed a 134-day annual monitoring period, a decreasing trend of 10% per year ($r = 0.10$) for 10 years, and parameter variances ranging from 1 to 6 times the estimated variances.

Another important issue is the relation of the population using a given haul-out (or set of haul-outs) to various populations of interest. In some cases, there may be interest in monitoring use of specific haul-outs for their own sake, and the population of interest will be the population using those haul-outs. However, if interest is in the population summering in Bristol Bay, for example, either all haul-outs in the bay must be monitored, or there must be some understanding of the pattern of walrus movements among haul-outs. Alternatively, if interest is in the Pacific walrus population, then there must be some understanding of walrus fidelity to Bristol Bay and how status of the primarily male summer population is related to status of the rest of the population.

5 ACKNOWLEDGMENTS

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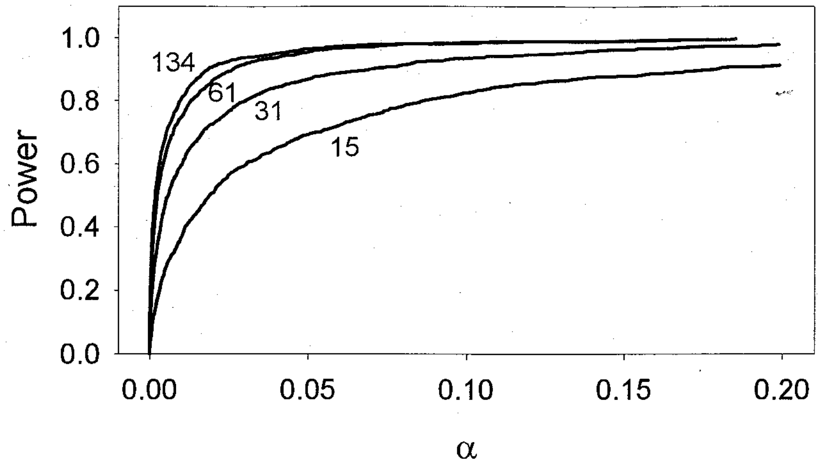

Figure 4. Power as a function of α-level for tests of trend based on $\hat{u}_i$. Data were generated with a more realistic version of model (2) that did not allow negative counts. The model assumed a decreasing trend of 10% per year (r = 0.10) for 10 years, parameter variances equal to estimated variances, and annual monitoring periods ranging from 15 to 134 days. All except for the 134-day monitoring period were centered on the expected day of the maximum adjusted count.

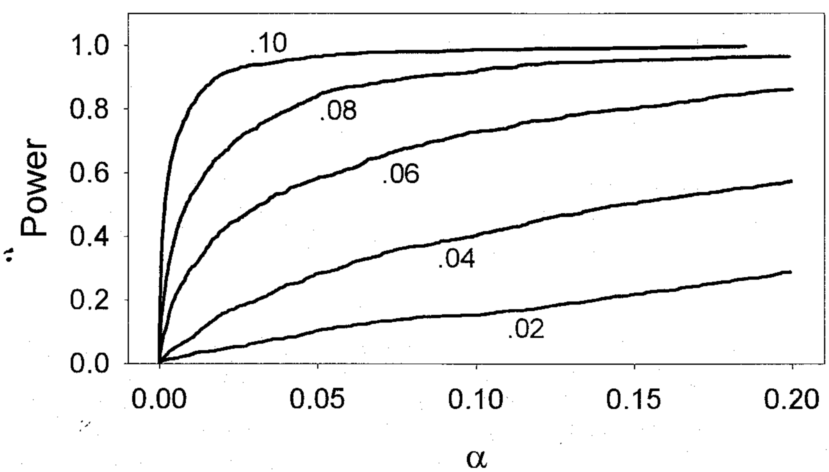

Figure 5. Power as a function of α-level for tests of trend based on $\hat{u}_i$. Data were generated with a more realistic version of model (2) that did not allow negative counts. The model assumed a 134-day annual monitoring period, parameter variances equal to estimated variances, and decreasing trends ranging from 2% to 10% per year (r = 0.02 - 0.10) for 10 years.

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