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Detecting Changes in Population Trends for Cook Inlet Beluga Whales (*Delphinapterus leucas*) Using Alternative Schedules for Aerial Surveys

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U.S. DEPARTMENT OF COMMERCE
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ABSTRACT

Measuring trends in population growth, and detecting a change in the trend, of Cook Inlet beluga whales (CIB) (*Delphinapterus leucas*) has a specific role in the co-management agreement that determines harvest levels and a more general application in the management of the population. The choice of an annual aerial survey schedule has an impact on both of these considerations. Detecting a change in trend in a population abundance time series which represents a change in the growth rate of the population and its vital rates involves two types of errors: Type 1 in which we conclude that a change in trend has occurred when it hasn't, and Type 2 in which we conclude that no change in the trend has occurred when it has. I examined the risk of each type of error in the context of five alternative survey schedules for the years after 2012: 1) annual surveys, 2) surveys on even years, 3) surveys every 3rd year, 4) surveys in the 4th and 5th years of a 5-year co-management period, and 5) surveys in the 3rd and 5th years of a 5-year co-management period. I also examined the impact of each of these schedules on our ability to identify a change point, the year in which a change in growth rate occurred.

A stochastic age- and sex-structured population model was used to project the population from 1994 to 2032 with two modifications: first a change in the birth rate and survival rate occurred in 2012 to increase or decrease the population's intrinsic growth rate by a fixed amount depending on the growth scenario; and second, an additional output was created for each model run to simulate a time series of aerial survey abundance estimates. The time series of simulated estimates were then analyzed to determine the probability of each type of error under each sampling schedule.

Twelve growth scenarios were considered: increases of 1%, 2%, 3%, 4%, no change, and decreases of -1%, -2%, -3%, -4%, -5%, -7%, and -10% per year. To test if a change in trend was indicated when none had occurred (Type 1 error), I used a linear regression of the natural logarithm of the estimated abundance on year to measure the trend and change in trend. The trend-change model assumes that the trend changes began in 2012. For each of the proposed schedules, the series of abundance estimates from the last 11 years (2002-2012) was used, then the alternative schedule for the years 2013 and later. For the measurement of the change in trend, I used a one tailed *t*-test with alpha = 0.05 to determine if the values for the change in trend were significantly different from zero. I also fit a model with no change in trend to the time series of

estimated abundance and used Akaike Information Criteria (AICc) to choose between the trend-change model and the no-change model. With no change in the growth rate of the population, there was an 8% to 22% chance that the estimated change would be significantly different from zero. The probability that the AICc would conclude that a change had occurred when there was no change in the growth rate was very low (< 3%).

Combining all of the growth scenarios into a single analysis, I found that for a given change in trend the alternative schedules would require 1 to 4 years longer to reliably detect the change than the annual schedule required. The range in which the annual schedule failed to reliably detect the change decreased from 0.019 (1.9%) after 10 years to 0.007 (0.7%) after 20 years. Meanwhile, the alternative schedules ranged from 2.2% to 2.9% after 10 years, an increase of 15% to 50% in failure to detect the trend change. The AICc analysis had a similar relative performance among the schedules, but the AICc required a change two to three times greater than the change found to be significant by the *t*-test in order to select the trend-change model over the no-change model.

For substantial declines of -10%, all schedules reliably identified the trend within 5 or 6 years. For the -7% and the -5% changes the annual schedule required 6 and 8 years, respectively, and in each case the alternative schedules required 2 to 4 additional to reliably (with 95% probability) identify a change in trend. For changes of ±3% or less, no schedule reliably identified the change in trend within the 20-year period, but the annual survey identified the change in more cases than alternative surveys by 20 to 30 percent in some examples.

Change point analysis showed 7 years spanned 95% of the outcomes for -10% change point and a decade for a ±4% change point in the every year survey schedule, thus this would be of little value to identify the year in which the change occurred.

Applying the subsistence strike algorithm used in the CIB co-management plans to the alternative schedules, I found no change in average take over the next 20 years for declining growth scenarios. For increasing scenarios, the bias in total average strikes resulting from the alternative schedules are small in comparison to the average take for the annual survey model. For the purpose of managing the hunt, the alternative schedules rank from most effective to least effective as: even year, 3rd and 5th year, 4th and 5th year, and every 3rd year. In the case of the detection of a change in trend, the even year schedule remains the best alternative schedule followed by the 3^{rd} and 5^{th} year schedule, then the every 3^{rd} year schedule, and last the 4^{th} and 5^{th} year schedule.

Much will depend on the types of management questions to be answered. In this context, the precision of alternative aerial survey schedules was evaluated but only in terms of setting subsistence hunt strike levels. The first consideration in selecting an alternative schedule was the detection of a change in trend. In this case, the even year schedule (Schedule 2) remained the best alternative, with the other alternative schedules showing similar performance to each other. The second consideration in selecting an alternative schedule was the length of the gap between surveys, in this case the 3^{rd} and 5^{th} year would rank next, then the every 3^{rd} year, and last the 4^{th} and 5^{th} year. Finally, the third consideration in selecting an alternative schedule should be whether the types of research conducted during non-aerial survey years would generate information with a value equal to or greater than the information lost in reducing the number of surveys.

CONTENTS

INTRODUCTION

Measuring population trends, and detecting a change in the trend, of Cook Inlet beluga whales (CIB), *Delphinapterus leucas,* has a specific role in the co-management agreement that determines harvest levels, and a more general application in the management of the population. Currently, an annual aerial survey schedule has provided abundance estimates from which growth trends for this population are determined. Under the harvest co-management agreement, the measured trend over a 10-year period is used to classify the population into one of three growth categories ("high", "intermediate", or "low"; Appendix). The growth category, along with the average abundance over the last 5-year period, is used to determine the number of takes allowed over the next 5-year hunting period (Appendix). For a more general application, we would like to be able to detect a change in the growth rate of the population that results from a change in the underlying life history parameters such as birth interval and rates of survival and identify the year that the change occurred.

Aerial surveys have been conducted over Cook Inlet each summer from 1994 to 2012, for the purpose of estimating abundance of beluga whales (Fig. 1). Flights took place during a 1-week to 2-week period each summer for 40-60 flight hours each year. Surveys followed a consistent protocol so that abundance estimates were comparable among years (Rugh et al. 2000, 2005, 2010; Hobbs et al. 2000a, b, In press). Precision improved with an increase in survey effort after 2001. Prior to 2001, the coefficient of variation (CV) for the abundance estimates ranged from 9% to 24% averaging 17% in the period 2002 to 2012, the CVs have ranged from 8% to 13% averaging 10%. For the purpose of this exercise, I used the period from 2002 to 2012 as the current trend period.

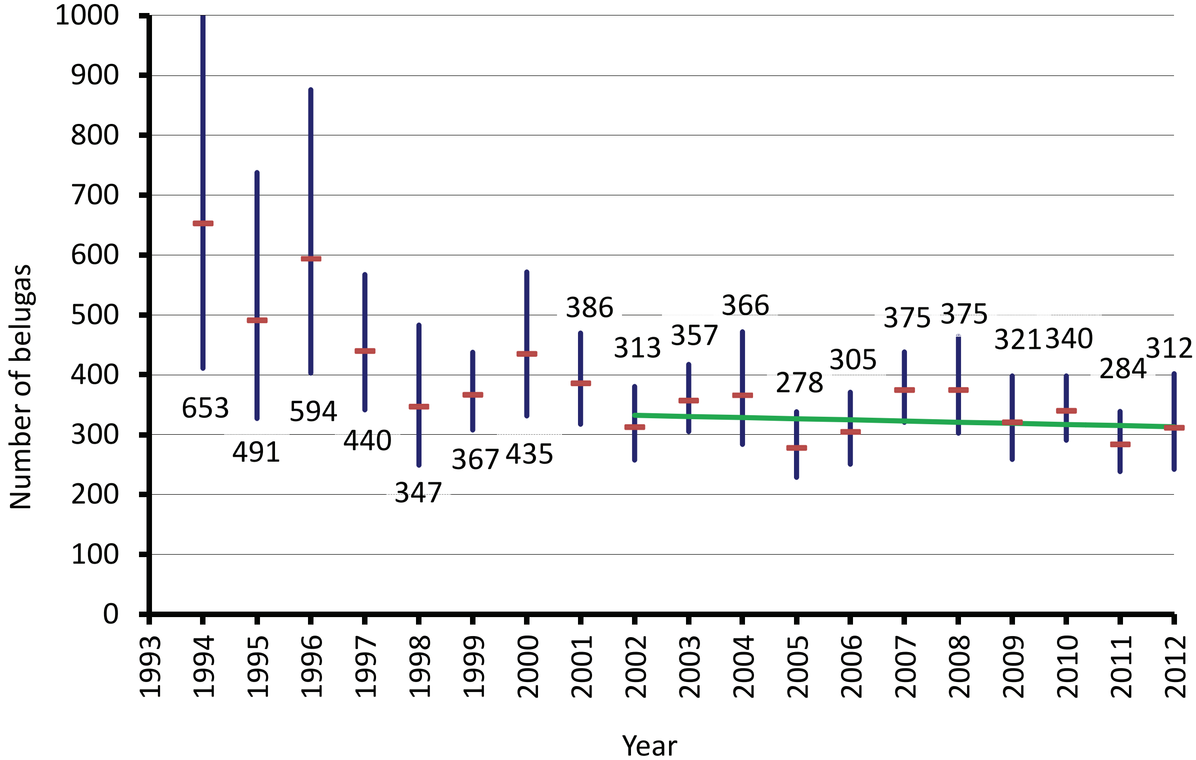

Figure 1.-- Abundance estimates for each year from 1994 to 2012. The red bars indicate the point estimates (numbers shown above and below the vertical blue bars). The vertical blue bars are 95% confidence intervals. The green line is the trend from 2002 to 2012 of -0.6% per year (SE = 1.1%).

SURVEY SCHEDULES

I considered five alternative schedules for aerial surveys beginning in 2012:

- Schedule 1: Continue the current annual survey without breaks.
- Schedule 2: Surveys conducted in even years only (i.e., 2012, 2014, 2016, etc.).
- Schedule 3: Surveys conducted every 3rd year (i.e., 2012, 2015, 2018, etc.).
- Schedule 4: Surveys conducted in the final 2 years (4th and 5th years) of each 5-year co-management period (i.e., 2012, 2016, 2017, 2021, 2022, etc.).
- Schedule 5: Surveys conducted in the 3rd and 5th years of each 5-year co-management period (i.e., 2012, 2015, 2017, 2020, 2022, etc.).

While Schedules 2 and 3 could begin any year, Schedules 4 and 5 are tied to the 5-year cycle of the co-management plan and thus have a first survey in 2012 to complete the 2008-2012 plans, with no surveys in the next 3 or 2 years, respectively (Table 1).

Table 1.-- Five alternative schedules for Cook Inlet beluga whale aerial surveys, 2012-2032. Blanks indicate a year with no survey.

	Schedule				
	1	2	3	4	5
Year	Annual	Even years	Every 3rd year	4th and 5th year of 5-year period	3rd and 5th year of 5-year period
2012	1	1	1	1	1
2013	2				
2014	3	3			
2015	4		4		4
2016	5	5		5	
2017	6			6	6
2018	7	7	7		
2019	8				
2020	9	9			9
2021	10		10	10	
2022	11	11		11	11
2023	12				
2024	13	13	13		
2025	14				14
2026	15	15		15	
2027	16		16	16	16
2028	17	17			
2029	18				
2030	19	19	19		19
2031	20			20	
2032	21	21		21	21

SIMULATED ABUNDANCE TIME SERIES

To test our ability to detect a change in trend in the current population, I generated a data set of abundance time series which included the uncertainty of the current population trajectory as well as demographic stochasticity using the age- and sex-structured, stochastic population model described in Hobbs and Shelden (2008) to project the population from 1994 to 2032. This model used binomial draws to include demographic stochasticity in the transitions of survival from year to year and births, includes density dependence in the parameters of survival and birth rates and accounts for losses of animals due to hunting. An initial set of 100,000 trajectories were developed using parameters drawn from uninformative priors for the population parameters, and initial population size and structure (see Hobbs and Shelden (2008) for details) were projected from 1994 to 2012.

A Bayesian sampling-importance-resampling (SIR) algorithm was employed to develop a posterior set of 2,000 population trajectories (cases) that are consistent with the abundance estimates between 1994 and 2012. From this point, the model of Hobbs and Shelden (2008) was used to project the population cases for each of the growth scenarios with two modifications: first a change in the birth rate and survival rate occurred in 2012 to increase or decrease the population's intrinsic growth rate by a fixed amount depending on the growth scenario; and second, an additional output was created for each model which includes an estimation error for each survey year drawn from the distribution of CV estimates from the surveys in 2002 to 2012 to simulate a time series of aerial survey abundance estimates. Thus, each trajectory in the posterior set was used to generate one case for each of the trend change scenarios comprising an abundance estimate time series which included the existing abundance estimates for 1994 to 2012 and the simulated estimates for the years 2013 to 2032. The time series of simulated estimates were then sampled according to the schedules in Table 1 to create the survey time series under each schedule for each case and growth scenario.

I used a relationship derived from the characteristic equation of the recursion model of the expected values of the population vector, Equation 4 of Hobbs and Shelden (2008) to determine *b,* the birth rate, from *s*, the survival rate, and φ, the intrinsic growth rate, Equation 5 of Hobbs and Shelden (2008).

$$b = \frac{2(1-s\varphi^{-1})}{s^{a_{mat}+1}\varphi^{-a_{mat}}} \quad ,$$

where, a_{mat} is the age of a female at first giving birth.

In the model of Hobbs and Shelden (2008), the growth rate and survival rates were drawn from uniform distributions and scaled using the logistic formula to account for density dependence. The values for the birth rate and survival rate for the period 2012 and later were determined using the equation above. First the increase or decrease in s, Δs, was drawn from a uniform distribution U[0, $\Delta\varphi$] with $\Delta\varphi$ being the change in the intrinsic growth rate for the scenario so that only a fraction of the change in growth rate resulted from a change in the survival rate. Then values of $\varphi_{2012} = \varphi + \Delta\varphi$ and $s_{2012} = s + \Delta s$ were substituted into the equation above to determine b_{2012}. The values for b_{2012} and s_{2012} were compared to the biological limits ($0.33 > b_{2012} > 0$ and $0.99 > s_{2012} > 0$) to determine if they were valid. If one or the other was found to fall outside of the biological ranges, a new value for Δs was drawn and the process was repeated. The birth and survival rates in 2013 and later were then calculated as before to account for density dependence then multiplied by b_{2012}/b and s_{2012}/s, respectively.

The abundance estimate time series, $\widehat{N}(y)$, for the years y = 2013+ and later was derived from the abundance $N(y)$ determined by the projection and a coefficient of variation, $CV(\widehat{N}(y))$, randomly drawn with replacement from the CV values for estimates from 2002 to 2012. The value for $\widehat{N}(y)$ was then drawn at random from a normal distribution with mean = $N(y)$ and standard deviation = $N(y)\ CV(\widehat{N}(y))$, truncated to ± 3 standard deviations to avoid outliers.

Twelve growth scenarios were considered: no-change, annual increases of 1% per year, 2% per year, 3% per year, 4% per year, annual decreases of -1% per year, -2% per year, -3% per year, -4% per year, -5% per year, -7% per year and -10% per year (Fig. 2). Note that the no-change model overlaps with the lower tail of the distribution for the +4% change scenario at its upper end and the -5% scenario at its lower end. Considerable uncertainty exists in the current population trend which was reflected in the distribution of the no-change scenario. The width of the distributions also accounts for the demographic stochasticity between 2012 and 2032 while the displacement from the no-change scenario represents the change in growth rate in 2012. The distributions are wider at negative growth rates resulting from the greater relative variability at smaller population sizes. After 20 years, the smallest population size of the scenarios with -10%/year change was less than 20 animals, while the largest population size of the scenarios with +4% change exceeded 700 animals.

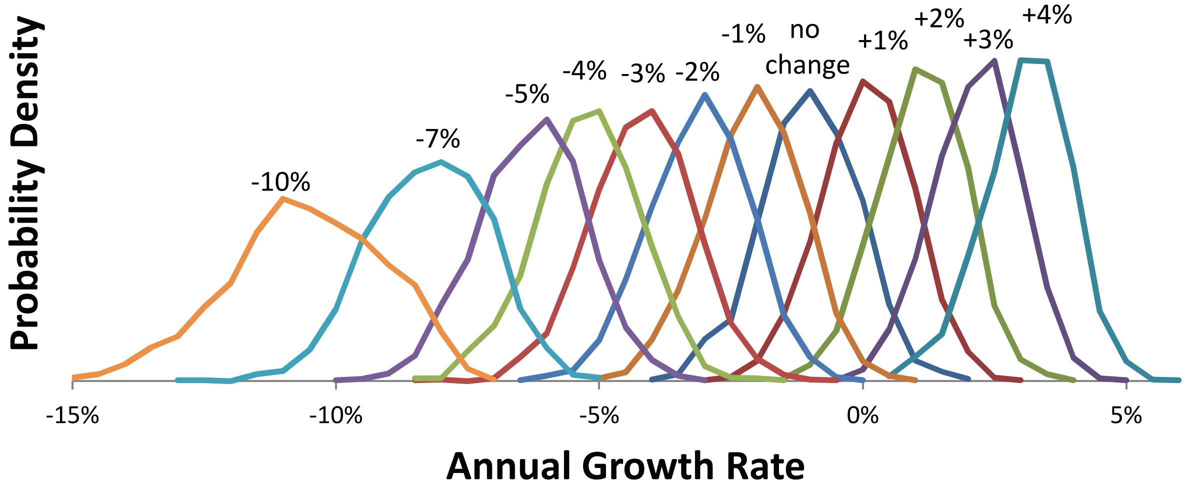

Figure 2.-- Posterior distributions for average annual growth rate from the population model over the period 2012-2032 for each of the 12 Cook Inlet beluga whale growth scenarios. The width of the distributions accounts for both the uncertainty of the current growth rate and the demographic stochasticity between 2012 and 2032 while the displacement from the no-change scenario represents the change in growth rate in 2012. The distributions are wider at negative growth rates resulting from the greater relative variability at smaller population sizes.

TREND ANALYSIS

The power of a statistical test relates to the ability to distinguish between two hypotheses, specifically it is the probability that the test will reject the null hypothesis when the null hypothesis is false (i.e., not commit a Type 2 error), and the alternative hypothesis is true. For this exercise, the null hypothesis was no change in trend occurred with the alternative hypothesis that a change in trend occurred in 2012. For a Type 1 error, I concluded that a change in trend occurred when it did not, and for a Type 2 error, that no change in the trend had occurred when it had. For the null hypothesis testing, I estimated the change in trend and employed a *t*-test (alpha = 0.05) to determine if the change was significantly different from zero.

I also employed a second approach using a model comparison statistic to see which model fit the data better -- the trend-change model or the no-change model. For both, I used a linear regression of the natural logarithm of the estimated abundance to measure the trend and change in trend. The trend-change model assumed that the trend changes beginning in 2012 so for each simulation, I fit the following model:

$$\ln(\widehat{N}_Y) = a + b\,Y + c\,Y_c$$

$$Y_c = \begin{cases} 0 \; for \; Y \le 0 \\ Y \; for \; Y > 0 \end{cases} \quad ,$$

where *a, b* and *c* are parameters that were fitted using least squares and *Y* was the year difference from 2012 so that *Y* for the years earlier than 2012 were negative and $\ln(\widehat{N}_Y)$ indicated the natural logarithm of the population estimate in year *Y*.

In this model, e^a was an estimate of the population size in 2012, *b* was the annual growth rate of the current 10-year trend (2002 to 2012), and *c* was the change in the annual rate after 2012 relative to the current trend. For each of the proposed schedules, the series of abundance estimates from 2002 to 2012 was used, and then the years indicated in Table 1 for the years 2013 and later. For the measurement of the change in trend, I used a one-tailed *t*-test with alpha = 0.05 to determine if the values for *c* were significantly different from zero. To determine whether the model with the change in trend was a better representation of the data than a single trend, I fit the no-change model:

$$\ln(\widehat{N}_Y) = a + b\,Y$$

to the time series of estimated abundance, and use Akaike Information Criteria (AICc) (Burnham and Anderson 2002) to determine the better fit. The AICc was a means to compare two models (Fig. 3). The *t*-test tested whether the change in slope at the bend in the blue line was significantly different from zero (Fig. 3). The AICc compared the red line and the blue line to determine which was more likely as a representation of the data, and identified which was the more likely representation of the data (Burnham and Anderson 2002, 2004), or in this case, whether to use the trend beginning from 2002 or that changes in 2012. With the limited number of data points, I included a correction for small sample size so that:

$$AICc = 2k\left(\frac{n}{n-k-1}\right) + n\left(\ln\left(\frac{RSS}{n}\right)\right) \quad ,$$

where k was the number of the parameters in the model including the variance (in this case either three or four), n was the number of survey years in the analysis, and RSS was the residual sum of squares s from the model fitting.

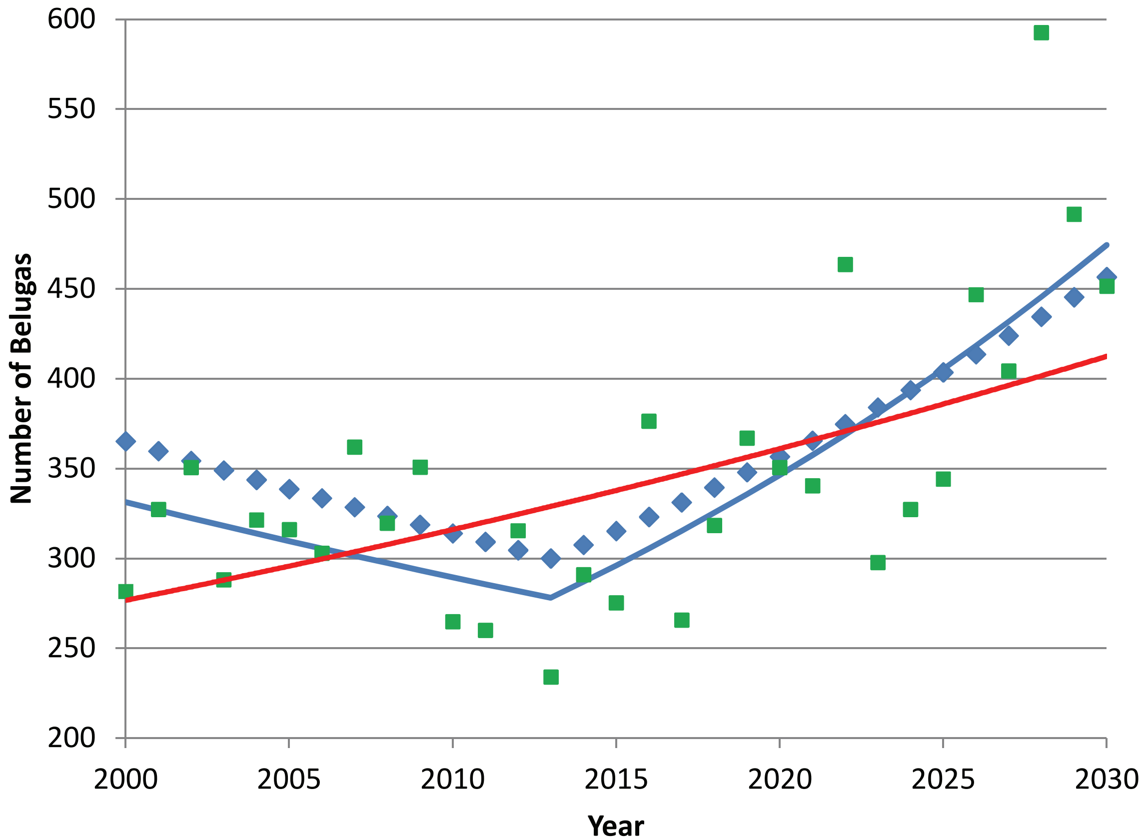

Figure 3.-- Example of fitted models for the Cook Inlet beluga population trends, the blue diamonds are the actual population abundance, the green squares are the simulated aerial survey estimates drawn for this example from a error distribution with a 10% CV, the red line is a single trend line fit to the 30 years of data, the blue line is Equation 2, fit to data.

Type 1 Errors

A Type 1 error occurred when the analysis indicated that a change in the trend had occurred when it had not. To investigate the risk of Type 1 errors, I used the no-change in growth scenario. With no change in the growth rate or life history parameters of the population, there was an 8% to 22% probability that the estimated value for *c* would be significantly different from zero (Table 2). This increased over time, probably as a result of the demographic stochasticity in the population model and was more likely in Schedule 1, with surveys in each year because of the greater number of data points. However, the probability that the AICc would select the trend-change model over the no-change model was very low (Table 2).

Table 2.-- Probabilities (as percents) of falsely concluding there had been a change in trend in the Cook Inlet beluga whale population. Each schedule was tested using a 1-tailed *t*-test (with alpha = 0.05) and the model comparison statistic AICc.

	Schedules tested using a 1-tailed *t*-test (alpha = 0.05)					Schedules tested using the model comparison statistic AICc				
Year	1	2	3	4	5	1	2	3	4	5
2017	10	8	7	8	8	1	1	1	0	0
2018	11	8	8	8	8	1	0	1	0	0
2019	11	8	8	8	8	0	0	1	0	0
2020	12	8	8	8	9	1	1	1	0	0
2021	13	8	9	9	9	1	1	0	0	0
2022	13	10	9	11	10	1	1	0	0	0
2023	13	10	9	11	10	1	1	0	0	0
2024	14	13	12	11	10	1	1	1	0	0
2025	15	13	12	11	12	2	1	1	0	0
2026	15	12	12	12	12	2	1	1	1	0
2027	17	12	13	13	13	1	1	0	1	1
2028	18	14	13	13	13	2	1	0	1	1
2029	19	14	13	13	13	2	1	0	1	1
2030	20	15	14	13	15	2	1	0	1	1
2031	21	15	14	14	15	2	1	0	1	1
2032	22	17	14	15	15	2	1	0	1	1

Type 2 Errors

The Type 2 errors depended on the magnitude of the change in trend to be detected. I investigated this first by considering the observed change in trend; that is, the estimated value for *c,* by combining all of the growth scenarios into a single analysis. I used logistic regression, with the probability of a significant value for *c* (using a 1-tailed *t*-test with alpha = 0.05) as the dependent variable and the the absolute value of *c* as the independent variable, to identify the estimated change in growth that was considered significantly different from zero in greater than 95% of cases for each of the five schedules (Fig. 4).

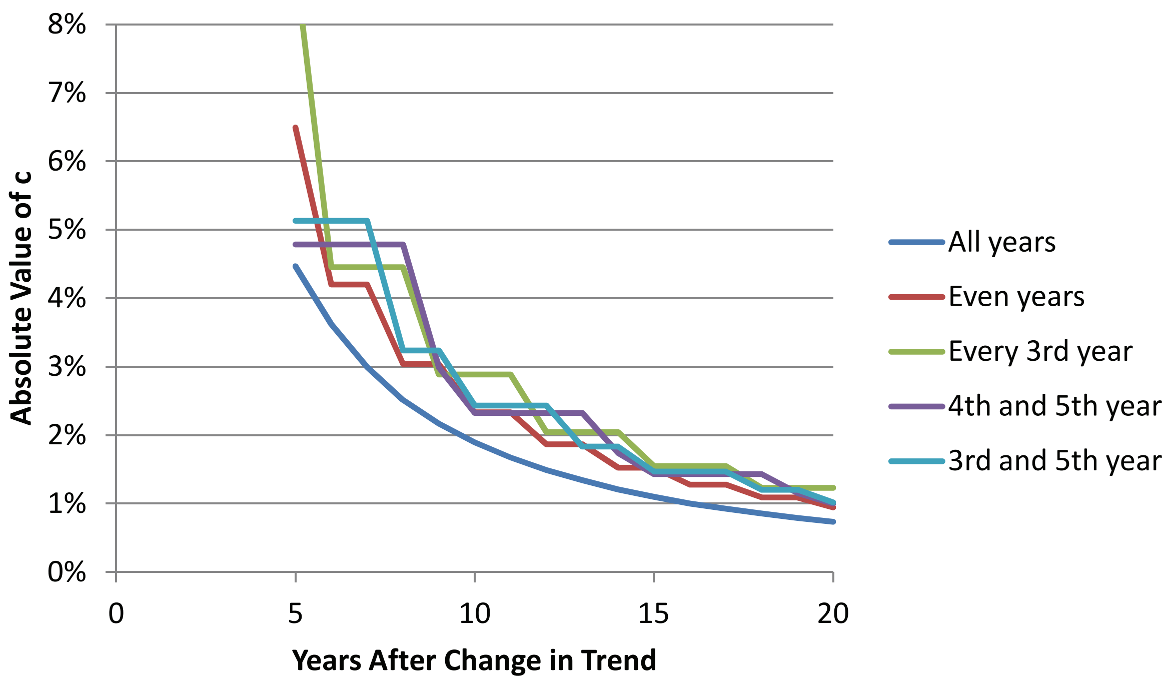

Figure 4.-- Absolute value of *c* (the change in the annual rate after 2012 relative to the current trend) at which *c* was significantly different from zero in 95% of cases by year after the change in trend and survey schedule. In the alternative schedules the horizontal segments occur for years with no survey.

Taking the point 10 years after the change in trend as an example, I found that an observed change of 1.9% or greater would be significantly different from zero (using a 1-tailed *t*-test with alpha = 0.05) in 95% of the cases. Moving to the right along the 2% change grid line, the alternative schedules do not reach this same level for 2 to 4 years depending on the survey schedule. Following vertically, at 10 years we see that the even year, 4th and 5th year, and the 3rd and 5th year schedules have a data point and have similar performance at 2.3%, while the every 3rd year schedule does not have a data point and falls at 2.9%. Thus, in general the range in which a Type 2 error would occur increases by 15% to 50% depending on the alternative schedule. Put another way, 1 to 4 additional years were required to achieve the same level of certainty when an alternative schedule was followed.

Examining a similar chart for the AICc analysis, we have a similar relative performance among the schedules (Fig. 5). However, the AICc was much less likely to select the trend-change model over the no-change model at all values of *c*. This results from the difference in analysis, whereas the previous analysis, the *t*-test of the significance of *c*, only looked at the magnitude of the change, this analysis considered the entire time series. For example, at 10 years the bent line model with a change of 5% between the first 10 years and second 10 years was being compared to a line that was fit over the change and would likely be 2.5% different from the slope during the first 10 years (cf. Fig. 2), thus the no-change model was accounting for some of the change in slope.

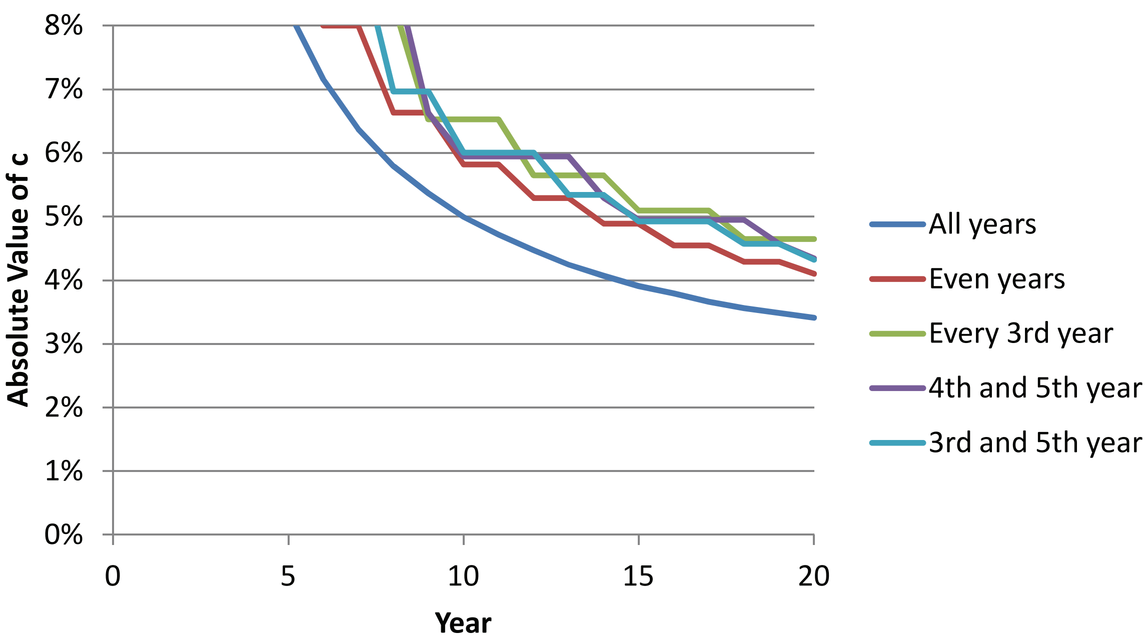

Figure 5.-- Absolute value of *c* (the change in the annual rate after 2012 relative to the current trend) at which AICc chose the trend-change model over the no-change model in 95% of cases by year after the change in trend for each survey schedule. In the alternative schedules the horizontal segments occur for years with no survey.

The analysis above demonstrated that an observed change in trend would be significant if it was sufficiently different from zero, but it was also important to detect an actual change in the growth rate itself. Of particular concern was a rapid decline. In Table 3, I examined the growth scenarios with changes of -5%, -7%, and -10% per year. The *t*-test for significance of *c* reaches the 95% level at 10, 7 and 5 years, respectively, for the three scenarios, with the alternative models reaching the same level of reliability up to 4 years later.

Table 3.-- Probabilities (as percents) that *c* (the change in the annual growth rate of the Cook Inlet beluga whale population after 2012 relative to the current trend) would be significantly different from zero (using a 1-tailed *t*-test with alpha = 0.05) for growth rate changes of -5%, -7% and -10%/year in the population model. The first year in which the probability exceeded 95% was indicated by a box.

Schedule	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
-5%																
1	71	84	92	$\boxed{96}$	98	99	100	100	100	100	100	100	100	100		
2	44	74	74	91	91	$\boxed{97}$	97	99	99	100	100	100	100	100		
3	27	70	70	70	93	93	93	$\boxed{98}$	98	98	99	99	99	100		
4	65	65	65	65	91	$\boxed{96}$	96	96	96	99	100	100	100	100		
5	62	62	62	88	88	$\boxed{96}$	96	96	99	99	100	100	100	100		
-7%																
1	89	$\boxed{96}$	99	100	100	100	100	100								
2	65	92	92	$\boxed{99}$	99	100	100	100								
3	41	90	90	90	$\boxed{99}$	99	99	100								
4	85	85	85	85	$\boxed{99}$	100	100	100								
5	81	81	81	$\boxed{98}$	98	100	100	100								
-10%																
1	$\boxed{98}$	100	100	100	100											
2	84	$\boxed{99}$	99	100	100											
3	58	$\boxed{98}$	98	98	100											
4	$\boxed{97}$	97	97	97	100											
5	$\boxed{95}$	95	95	100	100											

The AICc addressed a different question than the *t*-test for significance of *c* by comparing two representations of the no-change model, a single trend from 2002 to the year indicated or the trend-change model with a trend from 2002 to 2012 that changes in 2012 for the remainder of the time series. For example, if the change was, say, -10% beginning in 2012, the no-change model with a single trend for 2002-2022 may be -5% lower that the original slope from 2002 to 2012, while the trend-change model would have a change in slope closer to -10% at 2012 and for the years after. AICc was less responsive to the change and required one or two data points beyond that required by the *t*-test to select the trend-change model in 95% of the cases (Table 4).

Table 4.-- Probabilities (as percents) that the AICc will select the Cook Inlet beluga whale trend-change model over the no-change model by year for declining changes of trend of -5%, -7%, and -10%. Boxed cells indicate the year in which each schedule has a 95% or more probability of selecting the trend-change model.

Schedule	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
-5%																
1	29	45	60	73	82	89	93	96	97	98	98	99	99	100	100	100
2	10	31	31	57	57	75	75	86	86	92	92	96	96	98	98	99
3	5	27	27	27	57	57	57	80	80	80	91	91	91	97	97	97
4	22	22	22	22	54	71	71	71	71	86	92	92	92	92	96	97
5	19	19	19	50	50	70	70	70	85	85	92	92	92	97	97	98
-7%																
1	55	74	87	95	98	99	100	100	100	100	100					
2	21	58	58	86	86	96	96	99	99	100	100					
3	10	51	51	51	88	88	88	98	98	98	100					
4	45	45	45	45	85	95	95	95	95	99	100					
5	38	38	38	80	80	94	94	94	99	99	100					
-10%																
1	82	94	99	100	100	100	100	100								
2	44	86	86	99	99	100	100	100								
3	19	82	82	82	99	99	99	100								
4	75	75	75	75	99	100	100	100								
5	69	69	69	97	97	100	100	100								

As noted above, the AICc generally lagged behind the *t*-test of significance of *c* by a year or two. A similar pattern emerged in the scenarios with smaller changes in growth (Table 5), and, in fact, only the ±4% change was detected in 95% of cases before 20 years had passed, with the annual survey schedule reaching this level at 2024 or 12 years after the change, while the alternative schedules required 2 to 6 years more.

Table 5.-- Probabilities (as percents) that the estimated change in trend would be significantly different from zero (using a 1-tailed *t*-test with alpha = 0.05) for growth rate changes of ±1%, ±2%, ±3% and ±4%/year in the Cook Inlet beluga whale population model. The first year in which the probability exceeds 95% is indicated by a box.

Schedule	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
±1%																
1	13	14	17	20	22	23	25	27	29	31	33	34	35	37	38	40
2	9	11	11	15	15	18	18	21	21	23	23	26	26	29	29	31
3	7	10	10	10	15	15	15	20	20	20	23	23	23	26	26	26
4	11	11	11	11	15	18	18	18	18	21	24	24	24	24	26	28
5	10	10	10	14	14	17	17	17	22	22	25	25	25	27	27	30
±2%																
1	21	27	33	39	44	48	53	57	61	63	65	68	69	71	73	74
2	12	21	21	30	30	38	38	45	45	51	51	57	57	61	61	64
3	9	19	19	19	30	30	30	41	41	41	49	49	49	55	55	55
4	18	18	18	18	30	37	37	37	37	45	51	51	51	51	57	60
5	16	16	16	28	28	36	36	36	45	45	50	50	50	56	56	60
±3%																
1	35	46	56	65	72	76	80	84	87	89	90	92	92	93	94	94
2	19	36	36	52	52	65	65	73	73	80	80	84	84	87	87	88
3	12	32	32	32	54	54	54	68	68	68	78	78	78	83	83	83
4	30	30	30	30	51	63	63	63	63	73	79	79	79	79	84	86
5	27	27	27	48	48	61	61	61	72	72	79	79	79	84	84	86
±4%																
1	50	64	74	82	88	92	94	$\boxed{96}$	97	98	98	98	99	99	99	99
2	29	52	52	72	72	84	84	90	90	$\boxed{95}$	95	96	96	97	97	98
3	16	48	48	48	73	73	73	87	87	87	93	93	93	$\boxed{95}$	95	95
4	44	44	44	44	71	81	81	81	81	91	94	94	94	94	$\boxed{96}$	97
5	41	41	41	67	67	81	81	81	90	90	94	94	94	$\boxed{96}$	96	97

CHANGE POINT ANALYSIS

A change in survey schedule could also affect our ability to identify the year in which change occurred. This could be important to identify a mechanism that has permanently impacted the belugas of Cook Inlet such as a permanent change in habitat or the introduction of a regularly scheduled activity. For this analysis, I used the same model with the change in growth but rather than assuming that the change occurred in 2012, I considered the possibility that it could have occurred in any year or not all. I used the time series of abundance estimates for the period 2002-2032 and constructed 30 models, 29 with a change in each of the years from 2003 to 2031 and one with no change during the time period. The AICc statistic was calculated for each model and the change point with the lowest AICc value was selected (Western and Kleykamp 2004).

I applied this to the +4% and -4% scenarios combined in one, and the -5%, -7% and -10% scenarios and compared the precision to the change point estimates between the survey schedules (Table 6). For all schedules, the determination of the change point became more precise with a greater change in the growth rate. However, even with surveys every year, a change point for a -10% change in the growth rate with a standard deviation of 1.6 would have 95% of outcomes spanning 7 years, and a 4% change would have an interval spanning a decade, thus this analysis would be of little value to determine the year of the change in trend.

Table 6.-- Standard deviation in years of estimated change point selected using the minimum AICc model where a model with a change in growth rate was chosen over a no-change model for the Cook Inlet beluga whale population. The increase is the percent increase of the S.D. from the all year survey schedule (Schedule 1).

	±4%/year		-5%/year		-7%/year		-10%/year	
Schedule	S.D.	Increase	S.D.	Increase	S.D.	Increase	S.D.	Increase
1	2.9	0%	2.4	0%	2.2	0%	1.6	0%
2	3.4	15%	3.0	24%	2.4	9%	1.8	12%
3	3.7	28%	3.3	37%	2.6	19%	1.9	18%
4	3.7	28%	3.4	39%	2.6	20%	2.1	29%
5	3.6	22%	3.2	33%	2.5	13%	1.9	17%

SUBSISTENCE TAKE LEVELS

Subsistence hunting by Alaska Native hunters is managed under a co-management agreement. Take levels are determined by an elaborate algorithm which accounts for the observed trend, the recent population size, and the growth of the population since 1999 (Appendix). Using the average of abundance estimates over the previous 5 years and the distribution of the fitted growth rate of the previous 10 years, the population is assigned to one of 3 growth categories and one of 14 population size categories. Each of these growth and size categories has an assigned take level.

To test the performance of the different schedules, I used the time series of abundance estimates for each case of each growth scenario and applied the five survey schedules. I then used the algorithm as defined in the Cook Inlet beluga whale conservation plan (NMFS 2008: Option 2B, the prefered management option; Appendix), to determine the take level under each schedule for the 5-year management periods 2013-2017, 2018-2022, 2023-2027, and 2028-2032. I compared the alternative schedules by compiling the results for each growth scenario to determine the fraction of cases in which the alternative schedules recommended the same take levels as the annual survey schedule (Table 7). I also estimate the average difference in take resulting from using an alternative schedule (Table 8).

Table 7.-- The percentage of cases by growth rate change scenario and survey schedule in which the subsistence take under an alternative survey schedule matched the take when Cook Inlet beluga whale aerial abundance surveys occurred in all years.

	Schedules				
	1	2	3	4	5
Growth rate change	All years	Even years	Every 3rd year	4th and 5th year	3rd and 5th year
4%	100	66	53	52	56
3%	100	71	59	61	64
2%	100	77	68	72	73
1%	100	86	80	83	84
0%	100	94	92	93	93
-1%	100	98	97	98	98
-2%	100	99	98	99	99
-3%	100	100	99	100	100
-4%	100	100	99	100	100
-5%	100	100	100	100	100
-7%	100	100	100	100	100
-10%	100	100	100	100	100

Table 8.-- The average of total subsistence take of Cook Inlet beluga whales over the 20-year period (2013-2032) depending on growth rate change. Total take is shown for Schedule 1 (aerial surveys in all years) and the difference in average that occurs under the alternative survey schedules (Schedules 2-5). Note that no subsistence take occurs when the growth rate is negative.

	Schedules				
	1	2	3	4	5
Growth rate change	All years	Even years	Every 3rd year	4th and 5th year	3rd and 5th year
4%	31	-1	-3	4	2
3%	21	-1	-2	2	1
2%	12	0	-1	1	1
1%	5	0	0	1	1
0%	2	0	0	0	0
-1%	0	0	0	0	0
-2%	0	0	0	0	0
-3%	0	0	0	0	0
-4%	0	0	0	0	0
-5%	0	0	0	0	0
-7%	0	0	0	0	0
-10%	0	0	0	0	0

For the increases in growth rate of 3% and 4% after 2012, the simulated populations in most cases increase to between 500 to 650 belugas. According to the management table (Appendix), under this scenario the take increases with each increase of 25 animals. The abundance estimates in this range vary by as much as 75 animals from year to year, so it was quite likely that the average of two or three estimates would fall into a different bin from the average of all 5 years.

For the declining growth scenarios, all of the cases quickly declined to a population size that always fell into a zero-take range (Table 8) which explained the high percentage of correspondence among schedules. In all of the growth rate change scenarios, the even year surveys (Schedule 2) showed the most consistent performance compared to the annual surveys. The 3rd and 5th year schedule (Schedule 5) performed nearly as well despite having one fewer survey every 10 years.

With correspondence ranging from 52% to 100% (Table 7), the average takes were nearly the same (Table 8). There was a small negative bias (i.e., a lower take level) for the even year surveys and every 3rd year surveys (Schedule 2 and 3) and a slight positive bias in the two surveys that were based on the 5-year co-management interval (Schedule 4 and 5). The 4th and 5th year schedule (Schedule 4) showed the strongest positive bias as the growth rate increased, given under this scenario the two largest abundance estimates within each 5-year period would fall within the last 2 years. Thus, for the co-management process, the even year or the 3rd and 5th year schedules (Schedules 2 and 5) would be preferred.

DISCUSSION

The Cook Inlet beluga population is declining at an estimated rate of -1% per year. If this rate increased by 3% to a growth rate of +2%, we would consider the population to be recovering, If the population began to decline precipitously at a rate of -5% or lower, we would want to identify this situation quickly. These small changes in growth rate are difficult to detect given the abundance estimates have CVs of around 10% and the confidence interval for a 10-year trend is ±2%. To address this issue, I have considered two different approaches, the *t*-test of significance of the slope of the change in trend, and an AICc approach that considers which model, the trend-change or the no-change, best represents the time series.

The *t*-test resulted in a Type 1 error (a change in trend detected when none occurred) rates ranging from 8% to 22%, with the alternative schedules performing slightly better than the annual survey schedule. This was due mainly to fewer data points and reduced statistical power to identify such trends in those time series. The implication is that there is enough variability in the time series, so that the trend may have appeared to change with no actual change in the underlying population parameters. The no-change model was chosen in nearly all cases in all years and in all schedules when the AICc result was used, suggesting that it would be extremely difficult to detect a change in growth rate using this statistic.

The results for the Type 1 errors were consistent with the analysis of the significance of the observed trend (Figs. 4 and 5). The annual survey schedule was more likely to consider an observed change in trend to be significant than any of the alternative schedules for the same number of years or estimated value for *c* (the estimated change). The difference in the performance indicated that the alternative schedules would require 1-4 additional survey years to draw the same conclusion as the the annual survey schedule, or a 20%-50% greater change in trend to draw the same conclusion. The AICc required a much larger change in trend to reliably choose the trend-change model but showed the same relative behavior among the schedules.

The measurement of the observed trend demonstrates the precision of the analysis but does not address the probability of a Type 2 error. For substantial declines of -10%/year, all schedules gave a 95% probability of significant results (i.e., probability of Type 2 error < 5%) within 5 or 6 years. This was largely determined by the survey schedule since the even year and the every 3rd year schedules (Schedules 2 and 3) did not have a survey in the fifth year. For the -7% and -5% declines, the differences in performance were greater between the alternative schedules and the annual schedule with the alternative schedules requiring 2 to 4 years more, respectively, to reliably (at the 95% certainty) identify a change in trend.

The relative performance of the alternative schedules was determined largely by the number of data points in the time span under consideration with the even year schedule (Schedule 2) out performing the two surveys within 5-year schedules (Schedules 4 and 5), which out-performed the one in 3-year schedule (Schedule 3). The detection rates were similar at the ±4% to the results at -5%, probably due to a bias resulting from the time series of abundance estimates from 2002 to 2012. For changes of ±3% or less, no schedule reliably identified the change in trend but the annual survey was more reliable than the alternative surveys by 20 to 30 percentage points in some cases. Putting this in the context of a change in population size, if the population began growing at 3%/year (i.e., a 4% increase over the current trend) it would increase by 40% (to 437 belugas) in the 12 years required to show a significant change in trend with annual surveys, and by nearly 50% (to 468 belugas) in the 14 years required when surveys are on the even year schedule.

No schedule could reliably identify the change point. Consequently, other data and methods will be necessary if this is important to a particular management decision.

A well-defined management decision that relies on the trend in abundance is the subsistence hunt algorithm. This algorithm does not use the change in trend per se, but instead uses the measured trend over a 10-year period with a 5-year average of abundance estimates to determine the number of strikes. When the algorithm was applied to the alternative schedules, nearly all of the cases under declining growth rate scenarios matched results from the all years schedule. And when the total number of strikes was considered, all of the alternative schedules were equivalent to the all years schedule. For scenarios where growth rate was increasing, the percentage of correspondence was reduced both because of the greater absolute variability of the estimates and because the population size bins are reduced from 50 animals to 25 animals for populations between 500 and 650 animals. For all of the alternative schedules, the bias resulting from the alternative schedules was small (roughly 1 to 4 additional or fewer strikes). To manage the hunt, we can rank the alternative schedules from most effective to least effective as: even years (Schedule 2), 3rd and 5th year (Schedule 4), 4th and 5th year (Schedule 5), and every 3rd year (Schedule 3).

Much will depend on the types of management questions to be answered. In this context, the precision of alternative aerial survey schedules was evaluated but only in terms of setting subsistence hunt strike levels. The first consideration in selecting an alternative schedule was the detection of a change in trend. In this case, the even year schedule (Schedule 2) remained the best alternative, with the other alternative schedules showing similar performance to each other. The second consideration in selecting an alternative schedule was the length of the gap between surveys, in this case the 3rd and 5th year would rank next, then the every 3rd year, and last the 4th and 5th year. Finally, the third consideration in selecting an alternative schedule should be whether the types of research conducted during non-aerial survey years would generate information with a value equal to or greater than the information lost in reducing the number of surveys.

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APPENDIX

The algorithm for determining the Cook Inlet beluga whale harvest level using the 10-year trend and the 5-year average abundance, as presented in NMFS (2008:Ch. 2).

"2.3.2.3 Alternative 2 Harvest Schedule Under Options A and B

Other than the differences in timing when the harvest schedule is implemented, Options A and B are exactly the same as described in Steps A – C. References to Alternative 2 in the following pages of this chapter therefore refer to the details presented in Table 2-1.

I. NMFS will calculate the average stock abundance during the previous 5-year period.
II. NMFS will calculate the likely distribution of growth rate from the previous 10 years.
III. Using the abundance and growth figures obtained through Steps A and B, NMFS will calculate the probabilities that the growth rate within the population would be a) less than one percent, b) less than two percent, or c) greater than three percent. NMFS will then follow the decision tree below to select the proper category and harvest level outlined in Table 2-1.
    a. Is the average stock abundance over the previous 5-year period less than 350 beluga whales?
    If yes, Table 2-1 provides that the harvest is zero over the next 5-year period.
    If no, go to b.
    b. Is the current year 2035 or later, and is there more than a 20 percent probability the growth rate is less than one percent?
    If yes, the harvest is zero over the next 5-year period.
    If no, go to c.
    c. Is the current year between 2020 and 2034, and is there more than a 20 percent probability the growth rate is less than one percent?
    If yes, the harvest is set at three strikes over the next 5-year period.
    If no, go to d.
    d. Is the current year 2015 or later, and is there more than a 25 percent probability the growth rate is less than two percent?

If yes, go to Table 2-1 using the "Low" growth rate column.

If no, go to e.

e. Is the current year before 2015 and is there more than a 75 percent probability the growth rate is less than two percent?

If yes, go to Table 2-1 using the "Low" growth rate column.

If no, go to f.

f. Is there more than a 25 percent probability the growth rate is more than three percent?

If yes, go to Table 2-1 using the "High" growth rate column.

If no, go to the Table 2-1 using the "Intermediate" growth rate column.

Table 2-1. Alternative 2 Harvest Levels Under Options A* and B

5-year population averages	"High" growth rate	"Intermediate" growth rate	"Low" growth rate	Expected Mortality Limit
< 350	0	0	0	-
350-399	8 strikes in 5 years	5 strikes in 5 years	5 strikes in 5 years	21
400-449	9 strikes in 5 years	8 strikes in 5 years	5 strikes in 5 years	24
450-499	10 strikes in 5 years	8 strikes in 5 years	5 strikes in 5 years	27
500-524	14 strikes in 5 years	9 strikes in 5 years	5 strikes in 5 years	30
525-549	16 strikes in 5 years	10 strikes in 5 years	5 strikes in 5 years	32
550-574	20 strikes in 5 years	15 strikes in 5 years	5 strikes in 5 years	33
575-599	22 strikes in 5 years	16 strikes in 5 years	5 strikes in 5 years	35
600-624	24 strikes in 5 years	17 strikes in 5 years	6 strikes in 5 years	36
625-649	26 strikes in 5 years	18 strikes in 5 years	6 strikes in 5 years	38
650-699	28 strikes in 5 years	19 strikes in 5 years	7 strikes in 5 years	39
700-779	32 strikes in 5 years	20 strikes in 5 years	7 strikes in 5 years	42
780 +	Consult with co-managers to expand harvest levels while allowing for the population to grow			

* Option A would not be implemented until 2010.

I. At the beginning of each 5-year period, an Expected Mortality Limit is determined from Table 2-1 using the 5-year average abundance. During each calendar year, the number of beluga carcasses NMFS documents each year will be the mortality number for that year. If at the end of each calendar year this number exceeds the Expected Mortality Limit, then an unusual mortality event, as defined for these purposes, has occurred. The

Estimated Excess Mortalities will be calculated as twice the number of reported dead whales above the Expected Mortality Limit. The harvest will then be adjusted as follows:

a. The harvest level for the remaining years of the current 5-year period will be recalculated by reducing the 5-year average abundance from the previous 5-year period by the Estimated Excess Mortalities. The revised abundance estimate would then be used in Table 2-1 for the remaining years and the harvest level adjusted accordingly.
b. For the subsequent 5-year period, for the purpose of calculating the 5-year average, the Estimated Excess Mortalities would be subtracted from the abundance estimates of the years before and including the year of the excess mortality event so that the average would reflect the loss to the population. This average then would be used in Table 2-1 to set the harvest level.

II. If the Cook Inlet beluga population continues to experience less than one percent growth and well before the 5-year abundance average reaches 350 whales, NMFS will commit to seek funding for studies designed to determine whether the population is being affected by any of the following: 1) habitat destruction, modification, or curtailment; 2) over-utilization for commercial, recreational, scientific, or education purposes; 3) disease or predation; 4) inadequate regulatory mechanism; or 5) other natural or manmade factors affecting the continued existence of the Cook Inlet belugas."

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