



Kittlitz's Murrelet Monitoring in Glacier Bay National Park and Preserve 2010–2018

Synthesis and Program Review

Natural Resource Report NPS/SEAN/NRR—2019/1957





ON THIS PAGE

Lamplugh Glacier, a tidewater glacier in Johns Hopkins Inlet.
Image credit: NPS /STEVEN HOEKMAN

ON THE COVER

A Kittlitz's murrelet takes to flight.
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Executive Summary

Since 2010, the Southeast Alaska Inventory & Monitoring Network (“SEAN”) has monitored breeding season populations of Kittlitz’s (*Brachyramphus brevirostris*; “KIMU”) and marbled (*B. marmoratus*; “MAMU”) murrelets in Glacier Bay (“GLBA”) because of intrinsic conservation concern for these species and their role as integrators of marine and terrestrial ecosystems. The Glacier Bay National Park and Preserve Kittlitz’s Murrelet Monitoring Protocol (Hoekman et al. 2013a ; “Protocol”) specified objectives for each species of documenting population abundance and spatial distribution and of achieving 80% statistical power to detect 33% population decline over 15 years. My intent was to 1) summarize monitoring results and related research on murrelet species identification, 2) assess Protocol performance, adherence to key assumptions, and capacity to meet objectives, and 3) recommend enhancements to the Protocol.

Abundance estimates for KIMU (mean ~10,000, range ~7,000-16,000) and MAMU (mean ~63,000, range ~41,000-84,000) from line transect surveys during early July 2010-2018 have varied considerably but have greatly exceeded preceding estimates from strip transect surveys during mid-June 1999-2003 and 2008 (~125% increase for KIMU, ~500% for MAMU). The extent of differences in estimates among these and other studies resulting from differences in survey methods and timing or possibly from unknown bias in estimates (below) is uncertain. Nonetheless, it is reasonable to conclude GLBA has housed breeding season populations of global significance for both species. Regional movements in response to prey availability provided a plausible explanation for high annual variation abundance estimates and large increases relative to preceding estimates.

Spatial distributions of populations varied greatly among years and between species. Dense KIMU concentrations fluctuated annually among a few persistent “hotspots,” such as Reid Inlet, Beardslee Entrance, and the Hugh Miller-Skidmore Complex (see Chapter 1, Figure 1, 3). Upper reaches of glacially-influenced fjords received moderate use, but direct association with tidewater glaciers observed elsewhere in Alaska was limited. MAMU pervaded GLBA, but use strongly increased with proximity to its mouth. Extremely dense concentrations in lower GLBA likely included many “day commuters” entering GLBA to forage.

Line transect survey methods required observers to accurately estimate distances, a difficult task at sea. Training and assessment *via* distance estimation calibration trials supported that bias and variability in distance estimation error met performance goals, likely resulting in negligible bias in abundance estimates.

KIMU and MAMU are cryptic species (sympatric with similar morphology and behavior), creating risk of species misidentification (see Chapter 3, Figure 9) which can bias abundance estimates. The Protocol allows partial identification (to genus *Brachyramphus*) to avoid misidentification when identification is uncertain. Estimating species-specific abundance by pro-rating partially-identified individuals assumed equal species proportions in the identified and partially-identified samples, requiring survey observations to have no misidentification and equal probability of partial identification for each species.

The SEAN, in collaboration with the University of Montana, developed novel approaches employing photography to estimate mis- and partial identification (collectively “uncertain identification”). A 2013 field experiment led by Anne Schaefer indicated misidentification (range 1-5%) and partial identification (10-25%) declined with observer experience (1-5 years), with uncertain identification similar between species. In 2014, multi-observation methods applied by the SEAN during surveys found similar misidentification but substantially higher partial identification. These results, among the first for free-ranging vertebrates, indicated that observer experience reduced, but did not eliminate, uncertain identification and that critical statistical assumptions of Protocol methods were unsupported.

Potential bias in Protocol abundance estimates depends on magnitude of uncertain identification and relative true abundance of each species. Projections combining estimated uncertain identification with observed high abundance for MAMU suggested moderate to high positive bias in estimated KIMU abundance and low negative bias in estimated MAMU abundance. For relatively rare KIMU, positive bias increased substantially with higher misidentification, because many more of the common MAMU were misidentified as KIMU than *vice versa*. I concluded misidentification likely has been the dominant source of bias in Protocol abundance estimates. Large annual variation among observers and environmental conditions likely has resulted in large variation in misidentification and hence bias in abundance estimates. Nascent methods for estimating population abundance and spatial distribution of populations while accounting for uncertain identification are complex, data-hungry, and most effective when uncertain identification is low.

Estimates of statistical power were imprecise but suggested lower than desired power to detect population declines as a result of large annual variation in abundance estimates, which likely reflected both variation in true abundance and in bias from uncertain identification. The most viable remedy for high true variation is increased survey years. For relatively rare KIMU, high potential exists for misidentification to reduce power to detect decline, with catastrophic population decline potentially masked by escalating positive bias in estimated population abundance and trend. Achieving high capacity to detect decline will likely require mitigating biases by minimizing misidentification and statistically accounting for it when estimating population abundance and trend.

The Protocol has generally functioned as designed, but infrequent misidentification could undermine reliability of results. Minimizing misidentification is paramount (e.g., by improving training, reducing observation distances, improving optical equipment), but alone may be inadequate to eliminate misidentification and to limit bias in estimates of population abundance and trend. Statistical methods of estimating and accounting for uncertain identification can aid in minimizing bias. Necessary trials for estimating uncertain identification could be conducted during surveys or as separate experiments. Consideration of available resources, potential caveats, and necessary sample sizes will be essential to evaluating capacity of each alternative approach to meet Protocol objectives.



Braided waterfall in Tarr Inlet (NPS /STEVEN HOEKMAN)

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Glossary of Defined Terms and Acronyms

Defined terms and acronyms are denoted by quoted text enclosed by parentheses.

Assessments: Distance estimation calibration assessment sessions

Beaufort force: Positive integers of the Beaufort wind force scale describing wind speed and wave height.

***Brachyramphus* murrelets:** Murrelets belonging to genus *Brachyramphus*, including Kittlitz's and marbled murrelets.

Catastrophic decline: A population decline of 50% over ten years ($r = -0.069$).

CV{error}: The coefficient of variation (CV) in error among estimated distances relative to mean estimated distance, expressed as a percent (i.e., standard deviation of error / mean distance * 100).

GLBA: Glacier Bay

KIMU: Kittlitz's murrelet (*Brachyramphus brevirostris*)

MAMU: marbled murrelet (*Brachyramphus marmoratus*)

Moderate decline: A population decline of 33% over 15 years ($r = -0.027$); detecting such a decline is a Protocol objective for both murrelet species.

MOM: Multi-Observation Method, methods using classification of same murrelet groups by primary and secondary survey observers to estimate uncertain identification and true species proportions.

Observed angle: Survey observer's estimated angle to a murrelet group relative to the course of the line transect path.

Observed distance: Observer's visually estimated distance to a murrelet group detected during line transect surveys.

Observed species proportions: The proportion of murrelets classified as each species by primary survey observers.

Partial identification: Classification to the lowest certain taxonomic unit, genus *Brachyramphus*.

Percent error: The percent error in estimated distances relative to true distances.

Perpendicular distance: Length of a line perpendicular to the transect center line to a murrelet group.

Population decline: A declining trend in a population's abundance over time.

Primary (survey) observers: Boat-based observers acquiring data during line transect surveys.

Protocol: Glacier Bay National Park and Preserve Kittlitz's Murrelet Monitoring Protocol (Hoekman et al. 2013a)

Secondary (survey) observers: Observers classifying murrelets to species classes from computer images of murrelets recorded during line transect surveys.

Species misidentification: Classifying a murrelet as the incorrect species.

Schaefer methods: Methods developed by Schaefer et al. (2015) using classification of known-species murrelets to estimate uncertain identification.

SEAN: Southeast Alaska Inventory & Monitoring Network

True distance: Distance to target buoy (or murrelet) measured *via* laser range-finder.

True species probabilities: The probabilities that a murrelet belongs to each species.

True species proportions: The true proportion of each murrelet species in the sample population.

Uncertain identification: Collectively, species misidentification and partial identification



Kittlitz's murrelets carry fish kilometers inland to feed their chick at the nest. (NPS /STEVEN HOEKMAN)

Introduction

The Kittlitz's murrelet (*Brachyramphus brevirostris*, hereafter "KIMU") is a small, rare seabird endemic to Alaska and northeastern Russia (Day et al. 1999). Because of their role as integrators of marine and terrestrial ecosystems and intrinsic conservation concern, breeding season populations of KIMU and co-occurring marbled murrelets (*B. marmoratus*, "MAMU") in Glacier Bay National Park and Preserve were selected for the Southeast Alaska Inventory & Monitoring Network (SEAN) Vital Signs Monitoring Program (Moynahan et al. 2008). Building on prior surveys for these species (Lindell 2005, Drew et al. 2008, Kirchhoff 2008, Kirchhoff et al. 2010, Kirchhoff and Lindell 2011) in Glacier Bay ("GLBA"), the SEAN implemented a long-term monitoring protocol (the "Protocol", Hoekman et al. 2013a) with objectives (primarily for KIMU, secondarily for MAMU) of annual estimation of on-water abundance and spatial distribution for populations and of high power to detect 33% population decline over 15 years. After pilot surveys in 2009, boat-based line transect surveys (Buckland et al. 2001) consisting of an augmented, serially alternating panel design, with permanent transects sampled annually and panels sampled every third year, have been conducted using Protocol methods during early July 2010-2018.

The Protocol stipulated periodic assessment to assure monitoring performance and inform potential enhancements. My intent here was to:

- Summarize results of Protocol monitoring and related research activity.
- Interpret Protocol results in context of current scientific literature.
- Assess monitoring performance, key assumptions, and capacity to meet Protocol objectives.
- Provide recommendations for management of murrelets in GLBA and for potential enhancements to the Protocol.

This report is not intended to provide definitive estimates of species-specific density and abundance or estimates of trend in population abundance. Instead, I summarized results presented in annual monitoring reports pertaining to: species-specific abundance, spatial distributions of populations, estimation of detection probability, and conditions during annual surveys. I interpreted monitoring results in context of results from other surveys for these species, relevant scientific literature, and my assessment of Protocol performance.

Key assumptions of Protocol methods were tested using analyses of Protocol data and additional field experiments. Incomplete detection of murrelets compelled estimation of detection probability *via* line transect methods, which required assumptions about estimated detection functions and accuracy of distances estimated by survey observers (Buckland et al. 2001). Additional to evaluating robustness of estimated detection functions, I analyzed distance calibration assessment data collected during Protocol operations to assess performance of survey observers in distance estimation.

KIMU and MAMU are cryptic species (sympatric with similar morphology and behavior), which has often resulted in substantial partial identification (classification to the lowest certain taxonomic unit, genus *Brachyramphus*) during surveys and risk of species misidentification (misidentification and

partial identification are collectively “uncertain identification”). Misidentification has been unknown but posited to bias abundance estimates of coexisting populations (Hoekman et al. 2011c, Kirchhoff 2011, Piatt et al. 2011, Hodges and Kirchhoff 2012, Kuletz et al. 2013). Protocol methods attempted to limit risk of misidentification by allowing partial identification when species identity was uncertain. Partially-identified individuals are then pro-rated to estimate species-specific abundance; but, this approach required the critical assumption of accurate species identification. Two field experiments in GLBA used novel field and analytic methods to test this assumption, and I explore implications for monitoring.

Achieving desired statistical power to detect population declines largely depends on magnitude of annual variation in abundance estimates (Gerrodette 1987, Larsen et al. 2001). Evidence available during Protocol development suggested adequate probability of meeting these objectives, and I updated prior analyses using current monitoring results.

Finally, I applied available information to discuss options for managing murrelet populations in GLBA and potential enhancements to the Protocol. I organized this report into independent chapters:

- Chapter 1: Murrelet Monitoring Results 2010-2018
- Chapter 2: Distance Estimation Calibration
- Chapter 3: Species Identification and Abundance Estimation
- Chapter 4: Detecting Declines in Population Abundance
- Chapter 5: Summary and Recommendations

All chapters share defined terms, but each concludes with its own Literature Cited section. Chapters are best read in sequence. Chapter 5 contains main conclusions from each chapter and overall recommendations.

Chapter 1: Murrelet Monitoring Results 2010-2018

Annual reports described each year's survey activities and survey estimates (Hoekman et al. 2011a, b, 2013b, 2014, Sergeant et al. 2014, 2015, Sergeant and Johnson 2016, 2017, 2018). My intent here is to: summarize Protocol results in annual reports, assess Protocol field operations, interpret results in context of other surveys for these species and relevant scientific literature, and discuss implications for management of murrelets in Glacier Bay National Park and Preserve.

Methods

For most results, field and analytic methods matched those presented in the Protocol and in annual reports. Methods and study area differed slightly for pilot surveys in 2009, as described in Hoekman et al. (2011a). Summaries of spatial distributions also differed as described below. I estimated observer experience as the number of survey-years observers participated in similar population surveys for coexisting KIMU and MAMU prior to the current survey-year.

I also present summarized results from other population surveys for *Brachyramphus* murrelets in GLBA, and I refer readers to original sources for their methods. Various field and analytic methods have been used to account for uncertain identification. When possible, I selected abundance estimates that included pro-rated unidentified *Brachyramphus* murrelets. Some studies presented pro-rated abundance estimates only for KIMU and abundance estimates for total *Brachyramphus* murrelets. For these studies, I calculated MAMU abundance by subtracting KIMU abundance from total *Brachyramphus* abundance.

To summarize spatial distributions, I produced maps of mean estimated densities of survey observations of each species during 2010-2016. I segmented line transect into 1 km lengths, with terminal segments of 0.5 to 1.5 km to account for uneven transect lengths. For each survey year $y = 1$ to Y , n is the sum of observations of species s on transect segment t within the selected right-truncation distance w_y for each year. I estimated mean density d of observations for species s and segment t as

$$\hat{d}_{st} = \frac{1}{Y} \sum_{y=1}^Y \frac{n_{yst}}{2w_y l_t \hat{p}_y} , \quad (1)$$

where l_t is length of segment t and $\hat{p}_y$ is the estimated detection probability for year y . Transect segments not completely sampled in a given year were omitted from analyses. To visualize densities spatially, I plotted size-graduated symbols at the centroid of each segment. Including $\hat{p}_y$ and w_y controlled for year-specific differences in detection probability for murrelets. However, these methods did not account for uncertain identification, which could bias estimated densities (see Chapter 3). Therefore, estimated densities of observations were not estimates of true species-specific densities; instead, they are best interpreted as summaries highlighting relative differences in observations within a species across space.

Results

Sampling of survey transects in early July have typically been completed over a 9 day span (Table 1), with slightly over 7 days of sampling during that period and additional days of pre-survey operations. All target transects have been sampled each year, except passage along transect 025 in Johns Hopkins Inlet has often been partially impeded by sea ice (Figure 1). Observer experience varied widely among survey years.

Table 1. Timing, survey effort, and observer experience for line transect surveys for murrelets in GLBA, AK. Survey days is the number of days with transect sampling and observer experience is the number of survey-years for line or strip transects for these murrelet species prior to the current survey- year.

Year	Start Date	End Date	Survey days	Survey Effort (km)	Mean Observer Experience
2018	4 July	9 July	6	243	4.5
2017	6 July	10 July	5	251	2.0
2016	7 July	12 July	6	209	1.7
2015	9 July	16 July	8	250	0.8
2014	7 July	16 July	9	247	2.7
2013	6 July	13 July	8	214	2.5
2012	8 July	16 July	8	245	4.0
2011	5 July	16 July	7	258	2.0
2010	8 July	16 July	9	213	1.0
2009	8 July	15 July	8	219	0.0

Environmental conditions varied widely among survey years (Table 2), ranging from no precipitation to mostly precipitation. Mean Beaufort wind force (“Beaufort force,” a scale of positive integers

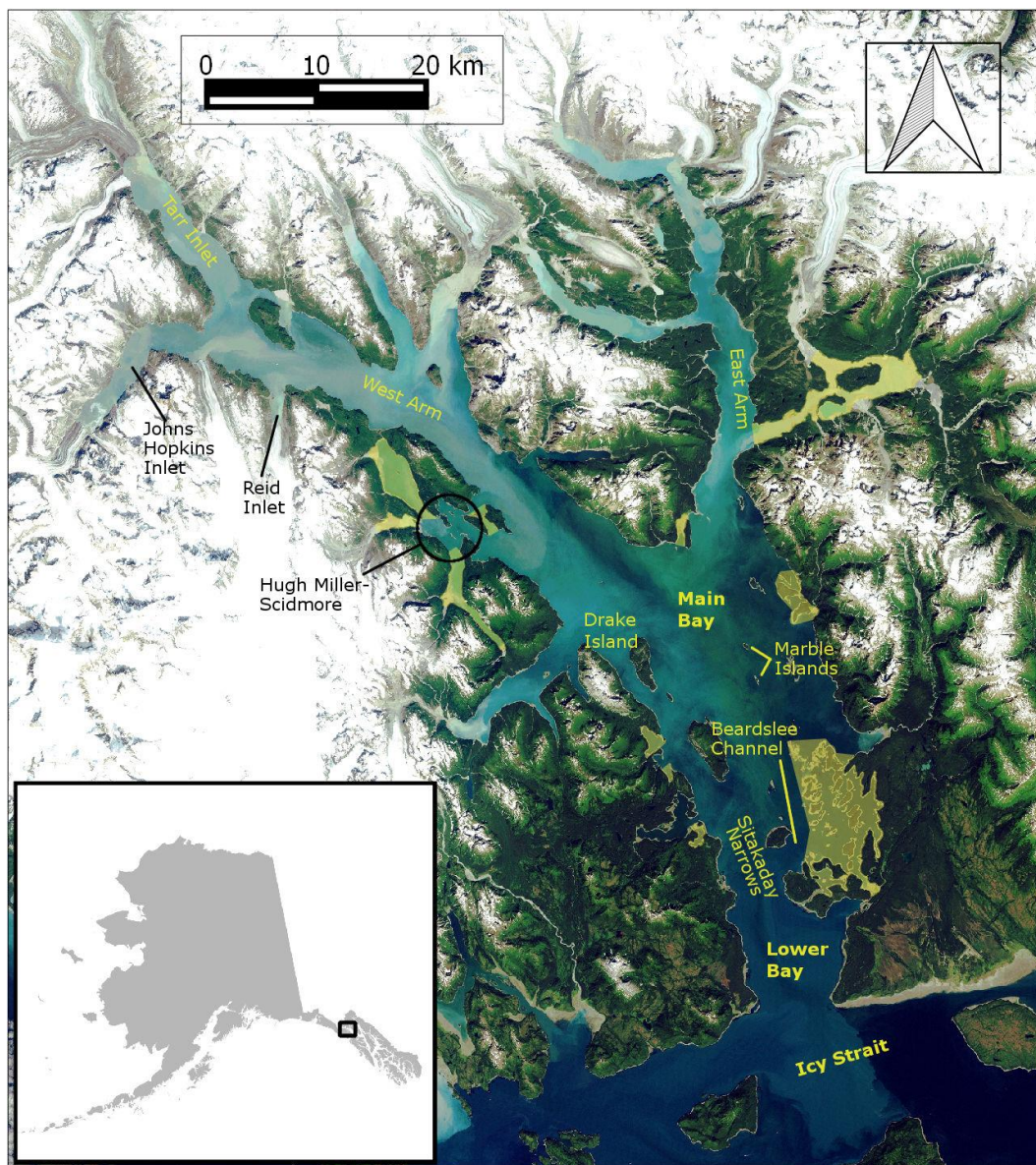


Figure 1. The Protocol's survey area includes 1,170 km² of waters north of the mouth of Glacier Bay, except areas shaded in yellow. Yellow and black labels highlight locations mentioned in the text.

Table 2. Parameters related to detection and identification of murrelets and to environmental conditions during line transect surveys in Glacier Bay, AK during early July. Detection parameters are derived from the estimated detection function. Weather categories and Beaufort wind force numbers record environmental conditions when murrelet groups were observed.

	% ID ^A	Detection			Weather (%)					Beaufort wind force (%)			
		Detection ^B (SE)	w ^C	ESW ^D	<50% CC ^E	>50% CC ^E	Fog	Mist	Rain	0	1	2+	Mean ^F
2018	91	0.62 (0.01)	200	123	50	44	6	0	0	58	40	2	0.44
2017	96	0.55 (0.02)	180	100	13	74	0	5	8	27	63	10	0.83
2016	91	0.67 (0.04)	180	121	50	43	0	1	6	60	39	1	0.41
2015	78	0.55 (0.01)	170	94	0	73	<1	26	1	39	48	13	0.74
2014	78	0.59 (0.01)	180	107	8	35	16	24	18	28	68	4	0.63
2013	85	0.71 (0.03)	190	135	15	72	<1	9	4	39	59	2	0.76
2012	62	0.71 (0.03)	200	145	4	76	<1	20	<1	16	54	30	1.14
2011	78	0.70 (0.02)	230	160	24	75	0	<1	<1	20	75	5	0.85
2010	76	0.72 (0.02)	230	144	29	49	0	21	2	69	26	5	0.36
2009	47	0.65 (0.02)	220	143	80	20	0	0	0	38	39	17	0.89
All	82	–	196	125	21	60	3	12	4	40	52	8	0.68

^A Percent of murrelet groups identified to species.

^B Estimated detection probability for murrelet groups within the right-truncation distance *w*.

^C Right-truncation distance *w* (distance from the transect center line beyond which groups were censored).

^D Estimated strip width (survey area effectively covered if detection probability were 1).

^E Estimated percent cloud cover of the sky.

^F Mean Beaufort wind force for survey observations.

describing wind speed and wave height) has varied by a factor of three annually, although force >1 has been rare. The percent of groups identified to species has ranged widely as well. Low crew experience and higher Beaufort forces were associated with low % identification.

The selected right-truncation distance *w* indicated the distance from the transect center line where estimated detection probability fell below ~0.15, and detection probability was estimated within this distance. Effective strip width (ESW) estimates width of the survey strip if detection probability were 1. Estimated detection probability showed relatively moderate variation among years, although lower estimates were associated with low observer experience and precipitation. Declining *w* and ESW over time in part likely reflects small changes in survey methods beginning in 2013 limiting observations at long distances (see Discussion for details).

Estimated on-water densities for KIMU, MAMU, and total murrelets (Table 3) and corresponding estimates of abundance within the survey area (Table 4) varied substantially annual among years.

Estimates ranged over 2-fold for KIMU and almost 3-fold for MAMU. Mean abundance was slightly over 10,000 for KIMU and more than 6 times greater for MAMU. Estimated abundance for each species showed no apparent trend or pattern (Figure 2).

Table 3. Estimated on-water population density of Kittlitz's, marbled, and total *Brachyramphus* murrelets in Glacier Bay, AK during early July, 2009-2018. Pilot surveys in 2009 differed in survey area and methods (Hoekman et al. 2011a) and were excluded from estimated means.

Year	Kittlitz's		Marbled		Brachyramphus	
	Density ^A	SE	Density ^A	SE	Density ^A	SE
2018	9.0	2.3	44.7	6.6	53.7	7.0
2017	7.5	1.3	50.5	7.2	58.0	7.3
2016	6.0	1.1	51.8	10.3	57.8	10.3
2015	9.2	2.2	71.6	10.3	80.8	10.5
2014	8.9	1.3	35.4	3.4	44.4	3.7
2013	6.2	1.7	72.2	13.2	78.4	13.3
2012	14.1	2.2	44.9	4.5	59.0	5.0
2011	6.4	1.0	63.1	6.0	69.4	6.1
2010	11.4	1.2	52.7	4.6	64.1	4.8
2009	12.0	3.7	26.5	3.7	38.5	5.2
All^B	8.7	0.9	54.1	4.3	62.8	4.0

^A Individuals/km²

^B Mean for years 2010-2018.

Table 4. Estimated on-water population abundance of Kittlitz's, marbled, and total *Brachyramphus* murrelets in Glacier Bay, AK during early July, 2009-2018. Abundance was projected across the survey area (1,170 km²). Pilot surveys in 2009 differed in survey area and methods (Hoekman et al. 2011a) and were excluded from estimated means.

Year	Kittlitz's		Marbled		Brachyramphus	
	Abundance	SE	Abundance	SE	Abundance	SE
2018	10,517	2,655	52,302	7,752	62,819	8,194
2017	8,810	1,513	59,126	8,390	67,936	8,525
2016	7,025	1,345	60,624	12,018	67,650	12,094

^A Abundance extrapolated over 1,092 km²; all others extrapolated over 1,170 km².

^B Mean for years 2010-2018.

Table 4 (continued). Estimated on-water population abundance of Kittlitz's, marbled, and total *Brachyramphus murrelets* in Glacier Bay, AK during early July, 2009-2018. Abundance was projected across the survey area (1,170 km²). Pilot surveys in 2009 differed in survey area and methods (Hoekman et al. 2011a) and were excluded from estimated means.

Year	Kittlitz's		Marbled		<i>Brachyramphus</i>	
	Abundance	SE	Abundance	SE	Abundance	SE
2015	10,778	2,598	83,793	12,044	94,571	12,321
2014	10,422	1,522	41,474	3,998	51,897	4,278
2013	7,210	2,046	84,428	15,394	91,638	15,529
2012	16,469	2,581	52,560	5,216	69,028	5,820
2011	7,477	1,119	73,766	7,055	81,243	7,143
2010	13,308	1,357	61,717	5,372	75,025	5,541
2009	13,124 ^A	4,062	28,978 ^A	4,077	42,102 ^A	5,755
All^B	10,224	1,074	63,310	5,042	73,534	4,717

^A Abundance extrapolated over 1,092 km²; all others extrapolated over 1,170 km².

^B Mean for years 2010-2018.

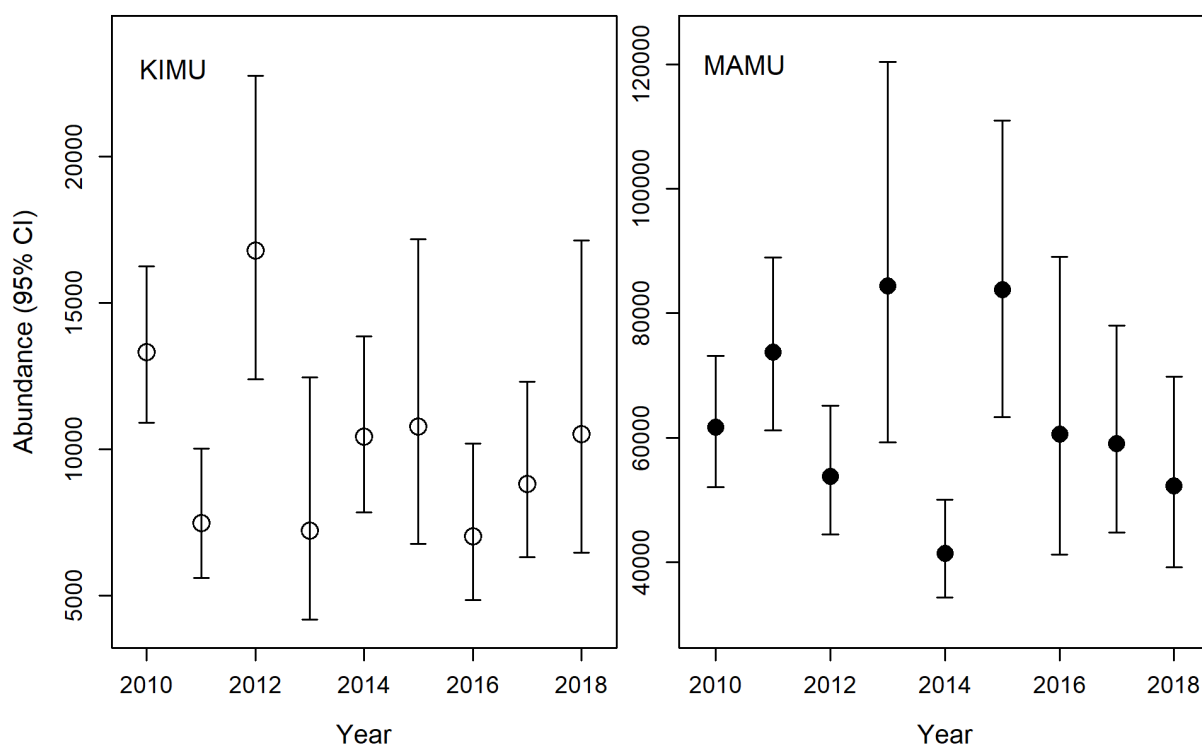


Figure 2. Estimated on-water abundance of Kittlitz's and marbled murrelets in Glacier Bay, AK during early July, 2010-2018.

Survey methods of other population surveys (Table 5) for murrelets in GLBA have varied between strip transects versus line transects, and survey timing generally spanned from mid-June to early July. All estimates of KIMU abundance included unidentified murrelets pro-rated according to proportions of each species in the sample of identified individuals. Abundance estimates for both species showed substantial annual variation. Apart from a very high estimate for 1991, estimated KIMU abundance fluctuated without apparent trend until an increase in 2010. Across all years, MAMU dominated total *Brachyramphus* abundance. Total abundance was high in 1991 and 1993, fluctuated at relatively low levels from 1999 to 2003 before increasing steeply beginning in 2007. In addition, most high total abundance estimates were for surveys in early July. For 2010, correspondence in estimates between concurrent Protocol and Kirchhoff and Lindell (2011) surveys was high.

Table 5. Estimated population abundance of Kittlitz's and total *Brachyramphus* murrelets from prior line transect and strip surveys in Glacier Bay, AK. I report abundance for marbled murrelets as total *Brachyramphus* minus Kittlitz's, because diverse methods were used to account for uncertain species identification. Source materials provide estimated sampling variances.

Year	Source	Survey type ^A	Timing	Kittlitz's abundance	Marbled abundance ^B	<i>Brachyramphus</i> abundance
2010	Kirchhoff and Lindell (2011)	line	early July	11,400	71,600	83,000
2009	Kirchhoff et al. (2010)	strip	early July	5,317	27,266	32,583
2008	Piatt et al. (2011)	line	mid-June	5,641	13,810	19,451
2008	Piatt et al. (2011)	strip	mid-June	3,583	NA	NA
2007	Kirchhoff (2008)	line	early July	4,299	31,318	35,617
2007	Kirchhoff (2008)	strip	early July	3,271	17,391	20,662
2003	Piatt et al. (2011), Drew et al. (2008)	strip	mid-June	4,394 ^C	12,203	16,597 ^D
2002	Piatt et al. (2011), Drew et al. (2008)	strip	mid-June	2,325 ^C	8,616	10,941 ^D
2001	Piatt et al. (2011), Drew et al. (2008)	strip	mid-June	4,735 ^C	10,244	14,979 ^D
2000	Piatt et al. (2011), Drew et al. (2008)	strip	mid-June	6,289 ^C	4,781	11,070 ^D
1999	Piatt et al. (2011), Drew et al. (2008)	strip	mid-June	5,536 ^C	10,467	16,003 ^D

^A Survey types are line transects (detection probability is estimated) and strip transects (assumes complete detection). Estimates from strip transects likely had substantial negative bias.

^B *Brachyramphus* murrelet abundance – Kittlitz's murrelet abundance.

^C From estimates of Piatt et al. (2011) that pro-rated unidentified murrelets.

^D From Appendix 5 of Drew et al. (2008).

^E Calculated as total counted murrelets x estimated KIMU abundance / (total counted KIMU + pro-rated KIMU).

Table 6 (continued). Estimated population abundance of Kittlitz's and total *Brachyramphus* murrelets from prior line transect and strip surveys in Glacier Bay, AK. I report abundance for marbled murrelets as total *Brachyramphus* minus Kittlitz's, because diverse methods were used to account for uncertain species identification. Source materials provide estimated sampling variances.

Year	Source	Survey type ^A	Timing	Kittlitz's abundance	Marbled abundance ^B	<i>Brachyramphus</i> abundance
1993	Kirchhoff et al. (Kirchhoff et al. 2014)	strip	early July	4,397	21,768	26,165
1991	Piatt et al. (2011)	strip	mid-June to mid-July	33,612	NA	NA

^A Survey types are line transects (detection probability is estimated) and strip transects (assumes complete detection). Estimates from strip transects likely had substantial negative bias.

^B *Brachyramphus* murrelet abundance – Kittlitz's murrelet abundance.

^C From estimates of Piatt et al. (2011) that pro-rated unidentified murrelets.

^D From Appendix 5 of Drew et al. (2008).

^E Calculated as total counted murrelets x estimated KIMU abundance / (total counted KIMU + pro-rated KIMU).

KIMU observations were distributed unevenly across GLBA, with sparse densities punctuated by “hotspots” with locally high densities (Figure 3). Notable hotspots included areas around Reid Inlet and Russell Island, the Hugh Miller-Skidmore Complex, the main bay east of the marble islands, and the Sitakaday Narrows near the Beardslee Entrance. Densities at hotspots varied widely among years. Moderate densities were also present in the upper reaches of glacially-influenced fjords.

MAMU observations increased with proximity to the mouth of GLBA (Figure 4). Densities were uniformly high in the lower bay, moderate across the upper main bay, and relatively sparse in the upper arms of GLBA. Annual variation was high for both species. For permanent transects, standard deviations of estimated densities of observations at each segment were on average about equal to and strongly correlated with the mean (Pearson $r = 0.91$ for KIMU, 0.93 for MAMU).

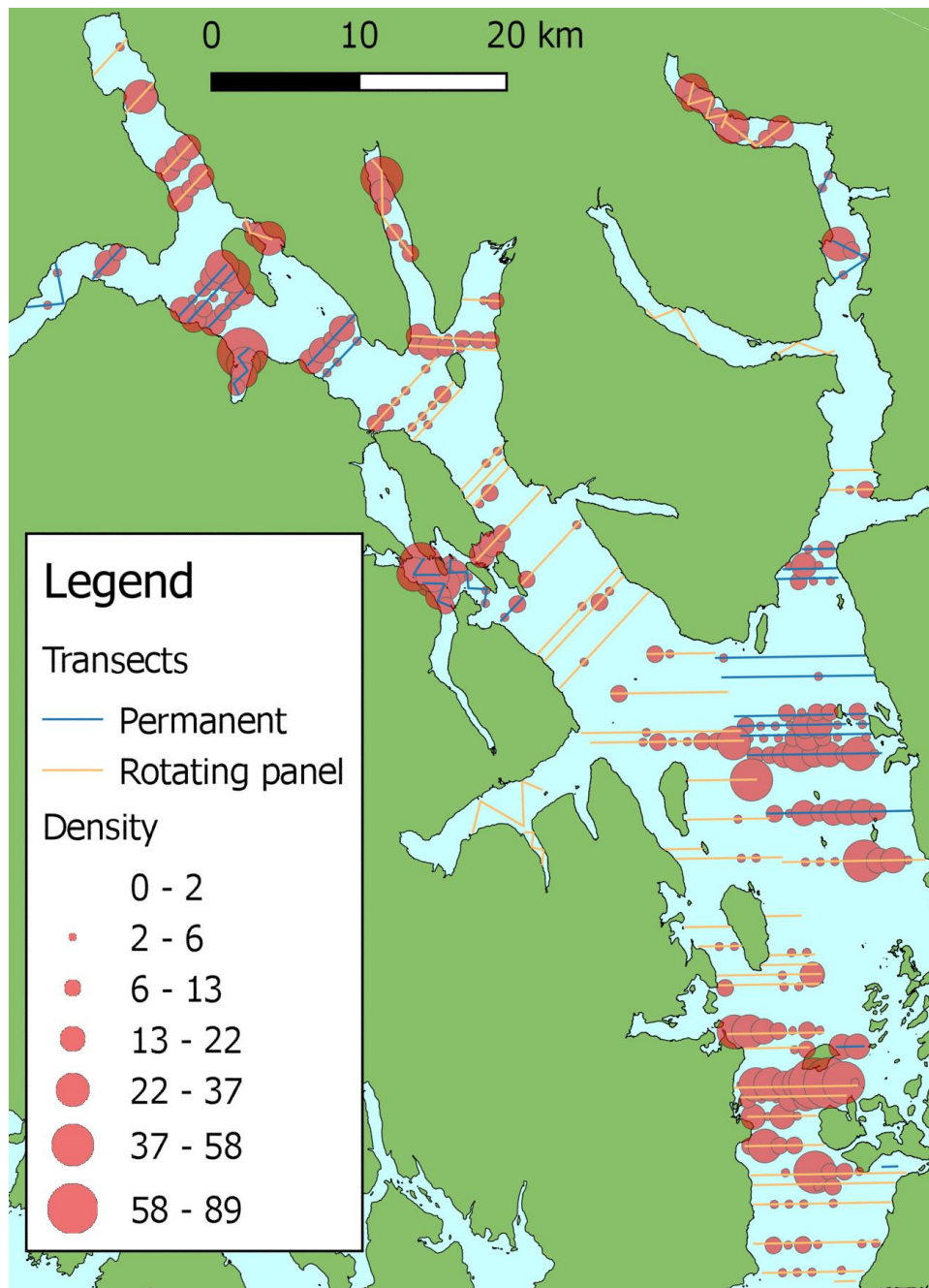


Figure 3. Mean estimated densities (individuals/km²) for survey observations of Kittlitz's murrelets in Glacier Bay, AK during early July 2010-2016. Permanent transects were sampled annually; rotating panel transects were sampled at 3-year intervals.

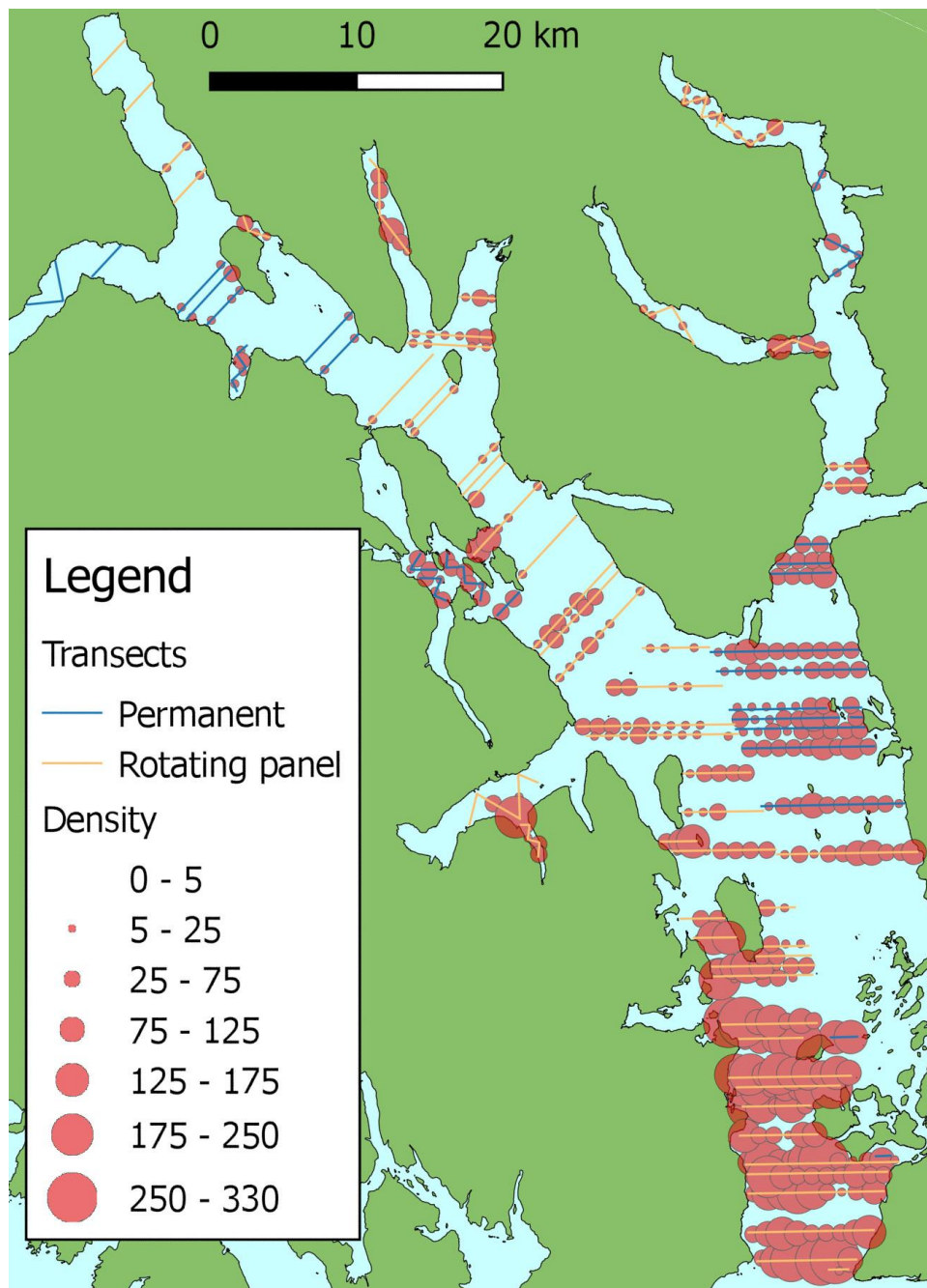


Figure 4. Mean estimated densities (individuals/km²) for survey observations of marbled murrelets in Glacier Bay, AK during early July 2010-2016. Permanent transects were sampled annually; rotating panel transects were sampled at 3-year intervals.

Discussion

Population Abundance

Protocol estimates indicated high on-water population abundance of *Brachyramphus* murrelets in GLBA, with MAMU typically far outnumbering KIMU and large annual variation for both species. However, a caveat to interpretation was that relative rarity of KIMU in concert with uncertain identification created potential for substantive bias in estimated abundance (see Chapter 3). Although magnitude of uncertain identification and resulting bias are largely unknown, analyses suggested potential for low, negative bias for MAMU and moderate to large positive bias for KIMU. Therefore, estimates presented here should be viewed as maximums for KIMU and minimums for MAMU.

One component of annual variation in estimates is sampling variance ($CV = 0.20$ and 0.15 for KIMU and MAMU), accounting for ~45% of total variation for both species (see Chapter 4). Another potential variance component is bias in abundance estimates arising from uncertain identification. Because uncertain identification likely varies considerably among years (see Chapter 3), differences in resulting bias may contribute to annual variation in abundance estimates. Large annual variation in true abundance also was likely, as these species have exhibited variable breeding propensity, low annual breeding-site fidelity, long-distance (>100 km) daily foraging commutes from nesting areas, and large annual changes in at-sea breeding season distributions. These traits may reflect a strategy of high mobility to exploit large spatial and temporal variation in prey availability (Bertram et al. 2015, Kissling et al. 2015b, Arimitsu et al. 2016, Kissling et al. 2016, Lorenz et al. 2017).

Comparing Protocol abundance estimates to others from GLBA and beyond introduces additional uncertainties. Differences in survey methods, design, coverage, and timing created differences in target populations and unknown bias in estimates. My assessment is limited to a few salient differences. First, strip transects assume certain detection, but estimated detection probabilities from line transect surveys (Kirchhoff 2008, Piatt et al. 2011, Table 2) indicated substantial negative bias in abundance estimates from strip transects. Second, diverse field and analytic methods have been applied to coping with uncertain identification (usually unknown), which has been hypothesized to bias abundance estimates (Kirchhoff 2008, Hoekman et al. 2011c, Kirchhoff 2011, Kuletz et al. 2011a, Piatt et al. 2011, Hodges and Kirchhoff 2012, this study, Kuletz et al. 2013). Finally, in-shore, on-water abundance of murrelets may increase from June to July in GLBA and elsewhere in Alaska, but magnitude and causes remain uncertain (Speckman et al. 2000, Romano et al. 2004, Kirchhoff 2011, Kissling et al. 2016, Stephensen et al. 2016).

Consonant with expectations, Protocol abundance estimates (early July line transect surveys) exceeded those from 1999-2003 and 2008 (for mid-June strip transect surveys); the extent to which increases (mean of ~125% and ~500% for KIMU and MAMU) reflected true population change versus methodological differences is unknowable. Difference in survey methods, which resulted in ~50% higher estimates for line versus strip transects in 2007 and 2008, were insufficient to explain increases. For MAMU, early July versus mid-June strip transects produced somewhat higher abundance estimates, suggesting that high Protocol estimates partly reflected seasonal effects. However, seasonal increases and intrinsic population growth appeared insufficient to account for observed increases. Bertram et al. (2015) attributed inter-annual variation in MAMU abundance

across sites in coastal western Canada to movement in response to prey availability, and such regional movements provide a plausible explanation for large variation in MAMU abundance estimates in GLBA.

In contrast, mid-June or early July estimates for KIMU did not show marked increase until 2009 to 2018, when MAMU were relatively abundant. Potential for positive bias in estimated KIMU abundance from species misidentification increases with their relative rarity, and even low misidentification can produce large bias when KIMU comprise <10% of *Brachyramphus* murrelets (see Chapter 3). I hypothesized that elevated MAMU abundance during 2009-2018 in combination with species misidentification likely elevated estimates for KIMU.

The U. S. Fish and Wildlife Service (2013) concluded KIMU populations in south-east and south-central Alaska declined from 1989-2000, but have since stabilized. Protocol abundance estimates are few for trend analyses but are consistent with the conclusion of no strong decline.

Interpreting Protocol abundance estimates in context of breeding season population estimates for other regions included uncertainty arising from differences in methods as well as large variation in uncertain identification and relative abundance of KIMU and MAMU. Given Protocol abundance estimates for KIMU greatly exceeded those for other locations, it is reasonable to conclude GLBA likely has accommodated the largest breeding season population in the region (Arimitsu et al. 2011, Artukhin et al. 2011, Day et al. 2011, Kissling et al. 2011, Kuletz et al. 2011a, b, Madison et al. 2011, Piatt et al. 2011). Relative to the current global population estimate for KIMU (~33,000, U. S. Fish and Wildlife Service 2013) and Alaska population estimate for MAMU (~270,000, Piatt et al. 2007b), breeding season populations in GLBA are of global significance for both species.

Spatial Distributions of Populations

Spatial distributions of murrelet populations observed during 2010-2016 were similar to prior GLBA surveys (Drew et al. 2008, Kirchhoff et al. 2010), but with heightened use of the lower main bay. All surveys have shown bay-wide distributions for MAMU, but increases in densities with proximity to the mouth of GLBA have been more extreme for Protocol estimates. Similar to others, Protocol surveys indicated moderate KIMU densities throughout upper fjords and high but variable densities in a few consistent, widely-spaced hotspots.

Aggregations at ephemeral foraging “hotspots” by murrelets and other avian predators may reflect prey availability (Kissling et al. 2007, Piatt et al. 2007a, Raphael et al. 2015, Urbanski et al. 2017). Inputs of cold, fresh water and silt in glacially-influenced marine ecosystems, resulting in increased turbidity and strong temperature and salinity gradients, can bring nutrients and invertebrates to the surface and increase availability of forage fish, and KIMU have been closely associated with and may be specially adapted for these habitats (Day et al. 2003, Kuletz et al. 2003, Kissling et al. 2011, Allyn et al. 2015, Grémillet et al. 2015, Arimitsu et al. 2016, Stempniewicz et al. 2017, Urbanski et al. 2017). In contrast to studies directly linking KIMU with tidewater glaciers (Kuletz et al. 2003, Renner et al. 2012, Allyn et al. 2015, Stephensen et al. 2016), KIMU in GLBA have typically not concentrated in immediate proximity of glacial outflow (Drew et al. 2008, Kirchhoff et al. 2010, this study). However, influence of glacial runoff may extend >10 km into fjords (Arimitsu et al. 2016).

In contrast, breeding populations of most MAMU and some KIMU have not been closely associated with direct glacial influence (Day et al. 2003, 2011, Piatt et al. 2007*b*, Madison et al. 2011). MAMU have concentrated far from glacial influence in lower GLBA in relatively shallow waters with strong tidal currents, and KIMU have aggregated specifically in Sitakaday Narrows, which is characterized by constricted flow, tide rips, mixing of waters from Beardslee Entrance, and underwater sills (Drew et al. 2013). Resulting upwelling and mixing of water and nutrients may aggregate prey and predators (Etherington et al. 2007, Arimitsu et al. 2016). Large concentrations of murrelets in the lower bay in part reflected daily influx and out flux of MAMU from Icy Strait, apparently travelling to exploit this foraging hotspot (Kirchhoff 2008).

Terrestrial habitat might also have influenced marine distributions. Recently de-glaciated land around upper reaches of GLBA provides sparsely vegetated or rocky nesting substrates used by KIMU (Kissling et al. 2015*a*, Felis et al. 2016, Kissling and Lewis 2016). Conversely, marine distributions of MAMU have been strongly linked to proximity of suitable nesting habitat provided by mature forest, such as that surrounding lower Glacier Bay (Raphael et al. 2015, Lorenz et al. 2016).

Rates of glacial loss in coastal southeast Alaska and GLBA have been high (Etherington et al. 2007, O’Neel et al. 2015). Although some have linked KIMU to advancing or stable tidewater glaciers, receding glaciers that discharge into marine waters may create foraging hotspots for piscivorous seabirds (Kuletz et al. 2003, Grémillet et al. 2015, Stempniewicz et al. 2017). Murrelet response to reduced direct glacial influence remains unknown (O’Neel et al. 2015, Arimitsu et al. 2016).

Marine traffic, particularly large cruise ships, accounts for most visitation to GLBA (Marcella et al. 2017). Marcella et al. (2017) found cruise ship passage disturbed murrelets within ~850 m, resulting in unknown energetic and demographic costs to ~20% of murrelets in GLBA. Disturbance from marine traffic in GLBA has temporarily displaced KIMU from foraging areas and substantially increased energetic expenditure (Agness et al. 2008, 2013). Agness et al. (2013) suggested high daily food needs and large energetic costs of provisioning nestlings placed breeding KIMU on the edge of their physiological capacity.

A regulatory option minimizing potential negative effects is limiting vessel disturbance in KIMU hotspots, especially near suitable nesting habitat (e.g. Reid Inlet, near Russell Island, Hugh Miller-Skidmore Complex) during the mid-June to mid-July nestling period when energetic needs peak (Day et al. 1999, Kissling et al. 2016). Cruise ships follow a predictable route (Figure 7 in Marcella et al. 2017), transiting Sitakaday Narrows and then passing just east of Drake Island and up the west arm to Tarr Inlet. Options minimizing disturbance of murrelets appear limited. Marcella et al. (2017) concluded that management-relevant factors (e.g., ship speed) didn’t influence disturbance, and I concluded that current routes likely avoided murrelet hotspots as much as practicable.

Because murrelets appear to be temporarily displaced by disturbance (Agness et al. 2008), “stacking” cruise ships by matching routes and timing to the greatest extent practicable may minimize disturbance to murrelets and other wildlife. However, this approach may be inconsistent with ship schedules and optimal visitor experience.

Flight of murrelets from cruise ships likely temporarily depresses murrelet density along the ship's path but increases density elsewhere. If flying birds settle on-water before affected areas are sampled, representatively sampling areas with altered densities will avoid biasing abundance estimates. About half of disturbed murrelets flushed and flew ≤ 2 minutes (Marcella 2014, Marcella et al. 2017), likely travelling < 2.5 km (assuming ~ 20 m/second). At minimum, I recommend avoiding sampling when cruise ships are < 2.5 km from the transect (~ 5 min of ship travel at 16 knots, Webb and Gende 2015).

Pilot studies indicated low to moderate species misidentification by survey observers, which could bias estimated spatial distributions (see Chapter 3). However, I felt it premature to apply complex methods to account for misidentification when estimating spatially-explicit densities, because magnitude and variation of misidentification existing in survey data are unknown. Analyses suggested low negative bias for MAMU, but low to moderate positive bias for KIMU that is likely positively correlated with local abundance of MAMU. Given these caveats, estimated densities of survey observations provide a useful tool for visualizing spatial distributions of each species.

Protocol Operations

Most Protocol operations appeared to be working as designed. Surveys have been completed in a timely manner, aside from expected difficulties with sea ice in Johns Hopkins Inlet and at times troublesome high winds. Termination of support for the Protocol's custom survey software application, NPTransect (Appendix F, Hoekman et al. 2013a), necessitated transition in 2016 to data acquisition using Park Observer, an ObjectiveC software application for iOS/iPad developed and maintained by the Alaska Region NPS GIS team. Park Observer utilizes a library from ESRI (Environmental Systems Research Institute, Redlands, California) to duplicate moving map functionality provided by NPTransect during surveys and outputs a nearly identical relational File Geodatabase including vessel track logs and observations. Although transition to Park Observer has been nearly seamless, necessary updates to the Protocol include replacement of Appendix F (NPTransect-KIMU Survey Tool) and substantial updates to SOPs 1 (At-Sea Surveys) and 4 (Corrected Observations (KM_D creation) to reflect changes to data acquisition and deliverables KM_C and KM_D. Revisions will require at least 5 days effort by the Data Manager. Additionally, revision of Chapter 4 (Data Handling, Analysis, and Reporting) will be needed to transition from disseminating deliverables on the SEAN monitoring web site to an authoritative NPS long-term monitoring repository (NPS Data Store). To facilitate potential future modeling of uncertain identification by survey observers (see chapters 3 and 5), it will be useful to add a data field to Park Observer to associate each observation with a specific observer and to log observer experience (defined above) of observers each year.

Estimated detection functions (see annual reports for each survey year) have met criteria for robust estimation of detection probability of murrelet groups by survey observers. High estimated detection probabilities have been beneficial for abundance estimation, with moderate declines in detection associated with increased precipitation or inexperienced observers. The percent of murrelet groups identified to species has generally fallen within recommended levels (Kirchhoff 2011), although low identification in 2012 suggested even experienced observers could not overcome unusually high Beaufort forces. Therefore, avoiding such conditions or providing observers with additional support

(e.g., image-stabilized optics, an additional observer assisting with identification) may be prescribed. Analyses of distance calibration data (see Chapter 2) indicated proficiency of survey observers in distance estimation. However, limitations in maximum distances used in training (a limitation of laser range-finders) as well as concerns about species identification for murrelet groups observed at long distances motivated a slight modification to observer methods. Beginning in 2013, observers did not record observations of murrelet groups beyond 200 m distance from the transect center line. I observed expected reduction in right-truncation distance w and ESW, but also unexpected decline in estimated detection probabilities, perhaps related to relatively high precipitation and low observer experience.



A harbor seal rests on drift ice. (NPS /STEVEN HOEKMAN)

Chapter 2: Distance Estimation Calibration

Estimates of density and abundance (hereafter, I refer only to density) from line transect surveys assume accurate perpendicular distances from the transect center line to animals (“perpendicular distances”; Buckland et al. 2001). For free-ranging animals, estimates often must be substituted for exact distances. The Protocol uses trigonometry to calculate perpendicular distance from observers’ visual estimate of distance and angle relative to the transect heading (“observed distances” and “observed angles”; see Hoekman et al. 2013 SOP 1 for full methods). At sea, sparse visual cues coupled with diverse environmental conditions hamper distance estimation, and error likely varies among observers and conditions (Oien and Schwender 1992, Gordon 2001). Bias in estimated density results from both mean error in perpendicular distances and variability in error (Chen 1998, Buckland et al. 2001, Borchers et al. 2010).

The Protocol’s distance estimation calibration methods serve to assure proficiency of survey observers in estimating distances to small targets at sea (Hoekman et al. 2013a SOP 9). Prior to and also daily during surveys, observers train and also demonstrate proficiency to meet performance goals during distance estimation calibration assessment sessions (“assessments”). Performance goals (below) were selected to minimize bias in density estimates.

My objectives were to:

- Summarize and assess performance during assessments.
- Identify factors meaningfully influencing distance estimation error.
- Assess implications for estimation of population density and trend.
- Recommend improvements to Protocol methods.

Methods

During distance estimation calibration (see Hoekman et al. 2013 SOP 9) observers estimate distances to small (murrelet sized, shaped, and colored) buoys, with true distances obtained *via* laser range-finder. I analyzed assessment data from the 2014-2016 survey years. During assessments, observers privately record estimated distances and don’t receive feedback on true distances. I assumed each observer’s estimates to be independent.

Let d_i be the i th estimated distance for $i = 1$ to I observations, with corresponding true distance t_i and distance estimation error $e_i = d_i - t_i$. The Protocol specified performance goals of <5% error (“percent error” = $I^{-1} \sum_{i=1}^I e_i / t_i * 100$) in mean estimates and <25% coefficient of variation in error among estimates (“CV{error}” = $\text{standard deviation}(\mathbf{e}) / \bar{\mathbf{d}} * 100$, where bold font denotes vectors of I observations).

To summarize overall assessment performance, I estimated percent error and CV{error} for each survey year and for each observer with a sample ≥ 25 . Next, I constructed linear mixed models (**lme4** package in R; Bates et al. 2015) exploring variables explaining variation in percent error for pooled data. I fit models using maximum likelihood methods and estimated confidence intervals using

likelihood profile methods. My goal was identify variables with pervasive, meaningful effects that could motivate improvements to Protocol methods. I hypothesized that individual observers, true distance, and environmental conditions might affect percent error. I included a random effect in all models to account for variation among observers and to compare the magnitude of inter-observer variation to fixed effects.

I used AIC_c (Burnham and Anderson 2002) and step-wise addition of variables for model selection. Because I felt true distance likely to be an important predictor, I first selected among 3 candidate models describing different functional responses of percent error: a constant model (t_i absent), a linear model (t_i included as linear covariate), and a polynomial model (t_i included as 2nd order polynomial). I then assessed whether Beaufort force and weather state (defined as in Hoekman et al. 2013 SOP 1) improved models. I suspected distance estimates would be positively related to the amount of visual cues (e.g., waves) between observers and targets and by visibility of targets. Therefore, I hypothesized a positive effect of Beaufort force, as increased waves would increase visual cues and partially obscure targets. I also hypothesized a positive effect of fog and rain, which decreased target visibility. I added Beaufort force as a categorical predictor (with 3 levels: 0, 1, 2) to the best candidate model above, and I selected this model if it reduced AIC_c . Fog and rain were only present in the 2014 data. Therefore, I repeated the above model selection procedures using only the 2014 data. I then added a weather state as a categorical predictor (with 3 levels: >50% cloud cover, fog, rain), and I selected this model if it reduced AIC_c .

Ideally, true distances during distance calibration should approximate observation distances during surveys. Therefore, I compared the mean and standard deviation of true distances from assessments versus observed distances during 2014-2016 surveys, excluding observations beyond right-truncation distances w (Table 2). Next, I assessed potential bias in density estimates, which can arise from mean error in perpendicular distances or variability of this error. Overall mean percent error was ~ 0 (below) and hence wouldn't affect density estimates. To assess potential effects of variation in error for observed distances on perpendicular distances and on density estimates, I applied bootstrap methods. I simulated error in perpendicular distances by drawing 10,000 pairs of random samples (with replacement) from errors e in observed distances and from observed angles during 2014-2016 survey data. I calculated error for each perpendicular distance as $\text{error} * \sin(\text{angle})$ and variation in error as the standard deviation of the resulting distribution. This approach assumed negligible correlation between errors and observed angles. I conducted analyses using the R statistical computing environment version 3.3.1 (R Core Team 2019).

Results

Mean assessment sample sizes exceeded 200 annually, with true distances ranging from ~ 30 -200 m (Table 6). Percent error and $CV\{\text{error}\}$ for each survey year were well within Protocol-specified goals. Overall percent error ~ 0 indicated absence of overall bias in distance estimates. Individual observers varied widely (Table 7), but estimates were imprecise. All observers were well within desired limits for $CV\{\text{error}\}$.

Table 7. Summarized results for 2014-2016 assessments, grouped by survey year. See text for definitions of true distances t , percent error, and CV{error}.

Year	$\bar{t}$	Min/Max t		Percent error	95% CI percent error		CV{error}	n
2014	90	27	190	2.9	1.2	4.7	15.3	303
2015	97	31	199	-2.9	-4.6	-1.1	12.1	163
2016	95	36	151	-3.1	-5.4	-0.8	13.4	175
All	93	27	199	-0.2	-1.3	1.0	14.3	641

Table 8. Summarized results for 2014-2016 assessments, grouped by observer. See text for definitions of percent error and CV{error}.

Observer	Percent error	95% CI percent error		CV{error}	n
1 ^A	-2.2	-3.8	-0.6	12.2	204
2 ^A	5.3	3.0	7.5	15.5	198
3	-0.2	-3.2	2.8	9.8	51
4 ^A	-4.6	-7.2	-2.0	12.5	77
5	-1.8	-6.0	2.4	16.1	88

^A Sample pooled across two survey years.

Parameter estimates from the selected mixed linear model of percent error supported a negative, linear effect of true distance and a positive effect of Beaufort force (Tables 8, 9a, 9b). The estimated random effect suggested that mean error for the 6 observers (i.e., $\pm 3.3\%$ in percent error around the mean error of ~ 0) was substantially below the specified limit of $< 5\%$, but uncertainty was large. Large residual variation indicated most variation was unexplained. Predicted (Figure 5) percent error for Beaufort force 0 and 1 declined from positive to negative with increasing true distance. Elevated predicted error for Beaufort force 2, largely reflecting 1 observer during 1 assessment trial, should be interpreted with caution.

Table 9. Model selection results for linear mixed models of variation in percent error in estimated distances for 2014-2016 assessments ($n = 641$). All models included a random effect describing variation among 6 survey observers.

Model	Model description	K^A	Deviance ^B	ΔAIC_c	AIC_c weight ^C
.	No distance covariate	3	-649.1	14.1	<0.01
t	True distance is linear covariate	4	-660.8	4.3 ^D	0.10
$t + t^2$	True distance is 2 nd order polynomial	5	-661.3	5.8	0.05
$t + \text{Beaufort force}$	True distance is linear covariate, Beaufort force is categorical predictor	6	-669.1	0.0 ^E	0.85

^A Number of estimated parameters.

^B Difference between 2 log(likelihood) for the current and saturated model.

^C Weight of evidence as the best approximating model.

^D Selected as best model of effects of true distance t .

^E Selected as final best model.

Table 10a. Parameter estimates for the selected best model of variation in percent error in observed distances for 2014-2016 assessment data.

Fixed effects	Estimate	95% CI	
Beaufort = 0 (Intercept)	0.023	-0.029	0.072
Beaufort = 1 (Intercept adjustment)	0.012	-0.012	0.035
Beaufort = 2 (Intercept adjustment)	0.069	0.022	0.117
True distance t (covariate)	-0.00051	-0.00087	-0.00016

Table 11b. Parameter estimates for the selected best model of variation in percent error in observed distances for 2014-2016 assessment data.

Random effect	SD	95% CI	
Observer (intercept adjustment)	0.033	0.017	0.072
Residual variation	0.142	0.135	0.151

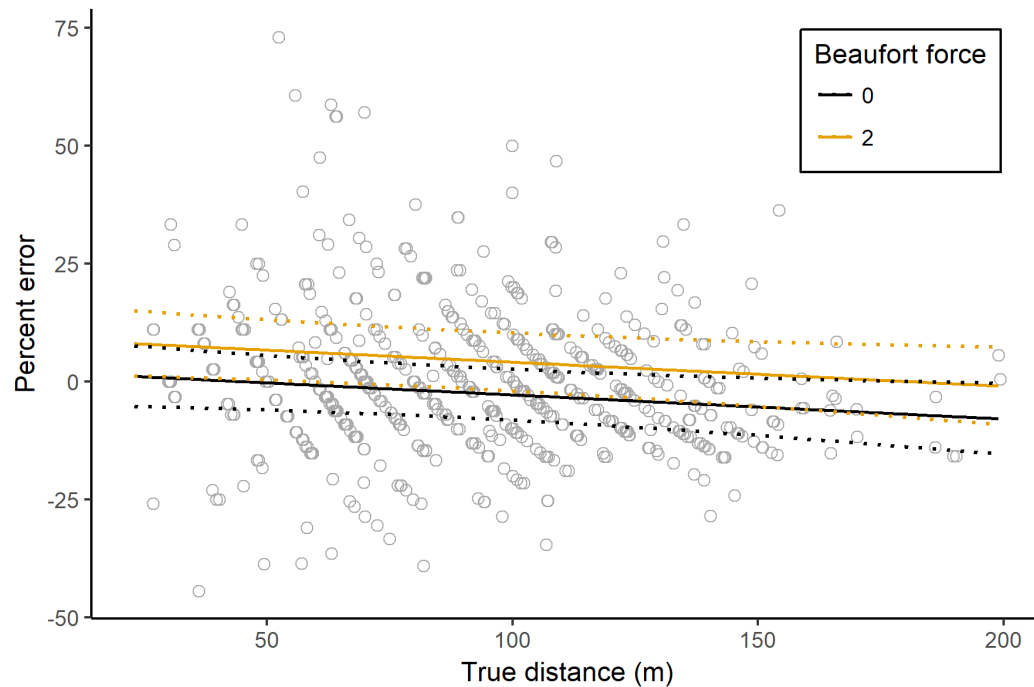


Figure 5. Predicted percent error in observed distances (with 95% confidence limits) relative to true distance and Beaufort force for 2014-2016 assessments. Predictions for Beaufort force 1 were slightly higher than force 0 and were excluded for clarity.

Variability in percent error was somewhat higher at shorter true distances. In part, this pattern can be attributed to rounding error resulting from observers' estimates being constrained to 10 m intervals. Such mild heteroscedasticity would be expected to impart slight positive bias to variance estimates, but not to bias parameter estimates. I chose to retain the current model for analyses, because my interpretation is most concerned with the magnitude of estimates and because of the ease of interpreting percent error (see below).

Model selection results for 2014 data also supported a linear effect of true distance (Table 10). Predictive effects of Beaufort force (including only forces 0 and 1) were unsupported. Effects of weather were strongly supported, and parameter estimates (Tables 11a, 11b) were similar to the 2014-2016 data. As hypothesized, percent error was higher for a limited sample during fog ($n = 54$, Figure 6). Contrary to expectations, little difference was seen between rain ($n = 108$) and cloudy weather (141). Mild heteroscedasticity was similar to that 2014-2016 data.

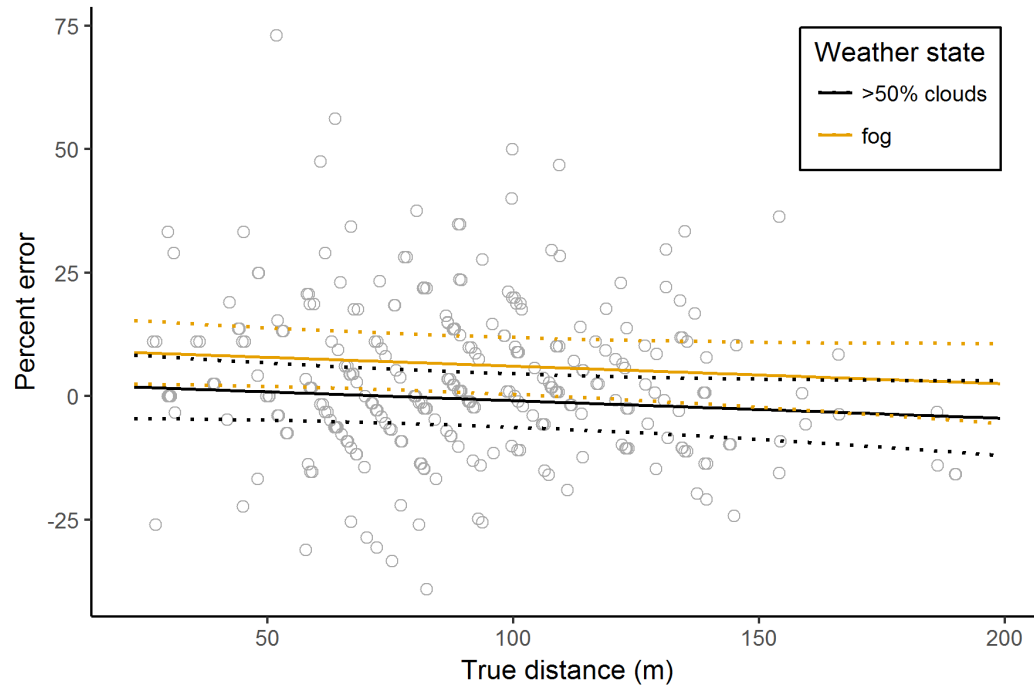


Figure 6. Predicted percent error in observed distances (with 95% confidence limits) relative to true distance and weather state for 2014 assessments. Predictions for rainy weather were slightly higher than for >50% cloud cover and were excluded for clarity.

True distances for assessment data were slightly shorter and less variable than observed distances from survey data (Figure 7), which included more distances >150 m. Most observed angles to murrelet groups for survey data were close to the transect heading (median = 35°, Figure 8), resulting in much shorter perpendicular distances relative to observed distances. A negligible correlation coefficient between observed angles and distances (Pearson $r = -0.05$) was consistent with assumptions. Bootstrap results indicated a standard deviation of 7.6 for errors in perpendicular distances projected from errors in estimated distances from assessments and from observed angles.

Table 12. Model selection results for linear mixed models of variation in percent error in estimated distances for the 2014 survey year ($n = 303$). All models included a random effect describing variation among 3 survey observers.

Model	Description	K^A	Deviance ^B	ΔAIC_c	AIC_c weight ^C
.	No distance covariate	3	-292.0	11.2	<0.01
t	True distance is linear covariate	4	-295.4	9.8 ^D	<0.01
$t + t^2$	True distance is 2 nd order polynomial	5	-296.7	10.4	<0.01
$t + \text{Beaufort force}$	True distance is linear covariate, Beaufort force is categorical predictor	6	-296.3	10.8	<0.01
$t + \text{weather state}$	True distance is linear covariate, weather state is categorical predictor	6	-309.2	0.0 ^E	0.98

^A Number of estimated parameters.

^B Difference between 2 log(likelihood) for the current and saturated model.

^C Weight of evidence as the best approximating model.

^D Selected as best model of effects of true distance t .

^E Selected as final best model.

Table 13a. Parameter estimates for the selected best model of variation in percent error in observed distances for 2014 assessment data.

Fixed effects	Estimate	95% CI	
>50% cloud cover (Intercept)	0.027	-0.056	0.108
Fog (Intercept adjustment)	0.070	0.033	0.107
Rain (Intercept adjustment)	0.012	-0.034	0.058
True distance t (covariate)	-0.00036	-0.00086	0.00014

Table 14b. Parameter estimates for the selected best model of variation in percent error in observed distances for 2014 assessment data.

Random effect	SD	95% CI	
Observer (intercept adjustment)	0.042	0.019	0.131
Residual variation	0.144	0.132	0.156

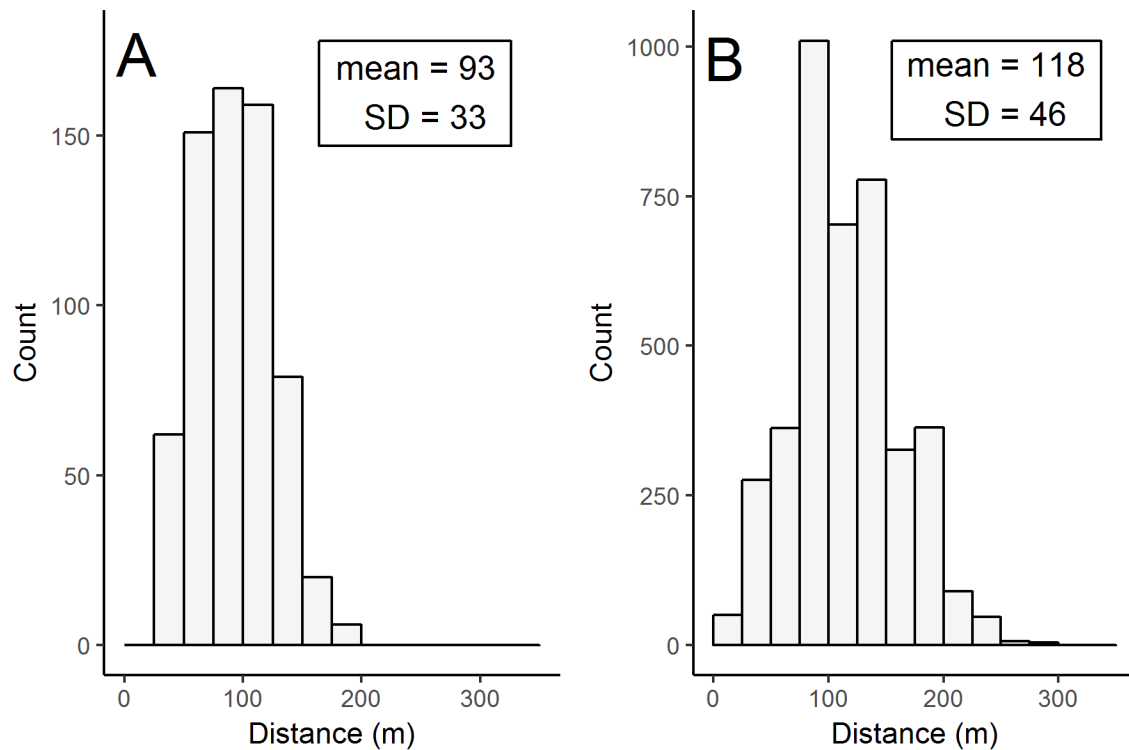


Figure 7. Distribution of A) true distances to targets during assessments and B) observed distances to murrelet groups during 2014-2016 murrelet monitoring surveys.

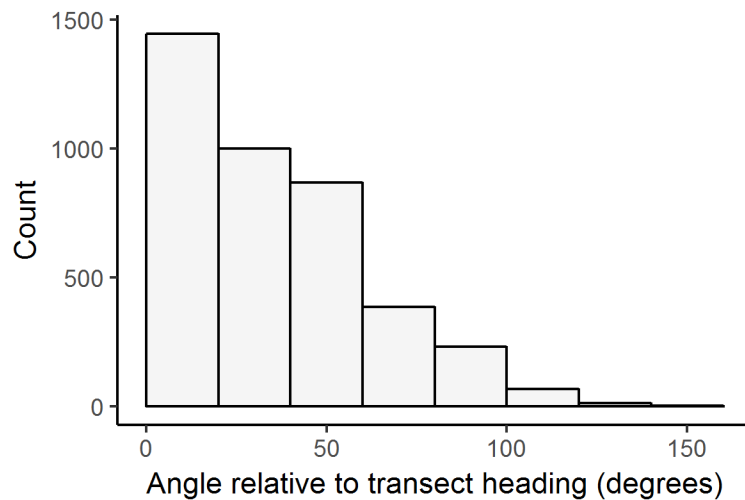


Figure 8. Distribution of observed angles to murrelet groups (0° to 180°, relative to the heading of the transect path) during 2014-2016 murrelet monitoring surveys.

Discussion

Visual estimation of distance at sea has often been plagued by high bias and variability, non-linear error relative to true distance, and large variation among observers and environmental conditions (Oien and Schwender 1992, Williams et al. 2007, Mateos et al. 2010), and error can have substantial

negative impact on bias and precision of distance sampling estimates (Chen 1998, Buckland et al. 2001, Borchers et al. 2010). Marine line transect surveys often estimate distances by measuring angles between animals groups and the horizon using reticles or images (Buckland et al. 2001, Gordon 2001, Williams et al. 2007). These methods likely are unsuitable for this Protocol, as effective reticle use depends on a stable vessel and image-based methods likely will produce similar or greater error than for visual estimates reported here because of a high ratio of wave-height to camera height in a small vessel.

Evidence supported that Protocol methods succeeded in developing proficiency in visually estimating distances, with overall performance meeting goals. Assessing individual performance was often hampered by modest samples and imprecise estimates. Large variation among observers and consistent bias have typified visual estimation of long-range distances (i.e., > 500 m, Oien and Schwender 1992, Mateos et al. 2010). However, despite moderate inter-observer variation, I concluded that most observers met performance goals and overall showed no consistent bias. Success likely reflected training and the relatively short distances typical of murrelet surveys (below).

Unusually dry, calm conditions during 2015-2016 surveys limited inference on effects of environmental conditions. Inconclusive evidence supported relative over-estimation of distances during foggy and windy conditions, consonant with predictions that increased visual cues and decreased apparent target visibility would inflate distance estimates. Evidence for relative under-estimation of distances at longer true distances was also tempered by sparse data for distances >150 m, reflecting limitations of rangefinders. Additional evidence to clarify these effects is warranted, although survey observations under these conditions are relatively rare.

Assessment performance is a surrogate to unknown performance during surveys. Given reasonable similarity in distances, target morphology, and environmental conditions, assessment performance is useful to gauging potential for bias in estimates of population density and trend. Bias in density estimates depends on error in perpendicular distances rather than observed distances. Absence of consistent bias in distance estimation error suggested no consistent bias in density estimates. Variability of error can negatively bias density estimates, but bias typically is small until average error approaches $\sim\frac{1}{2}$ the width of the shoulder of the estimated detection function (Chen 1998). Bootstrap simulations projected that errors in perpendicular distances (standard deviation = 7.6) likely comprised only a small fraction of the typical shoulder width (~ 60 m) of detection functions for survey data (Hoekman et al. 2011a, b, 2013b, 2014, Sergeant et al. 2014, 2015, Sergeant and Johnson 2016, 2017, 2018), suggesting minimal bias.

Recent acquisition of Leica range-finding binoculars by the SEAN presents opportunity to calibrate distance estimates to murrelets and to assess error in distance estimates during surveys. It would be useful to explore under what conditions distances to murrelets can be reliably measured.

Percent error in observed distances typically will result in an opposite but similar percent bias in density estimates (e.g., 10% error in distances creates bias of $\{100 * [1 - (1/1.1)]\} = -9\%$ in density estimates). Percent error for varied slightly annually, apparently reflecting differences among observers and environmental conditions. These results imply annual density estimates had small but

not negligible bias. If bias across years is randomly centered on 0, estimation of population trend would be largely unbiased but power to detect population decline would be slightly decreased by elevated annual variation in abundance estimates.

Annual distance calibration results could be applied to statistically adjust density estimates, but I feel this approach likely not useful because 1) potential bias in density estimates arising from error in distance estimation likely is small and tends toward 0 and 2) distance calibration assessments provide an imperfect surrogate to survey performance, and 3) calibration results are imprecise.

Conclusions

- Distance estimation calibration methods succeeded in developing and demonstrating proficiency of survey observers in visually estimating distances at sea, with overall performance meeting Protocol goals.
- Despite imprecision impeding assessment of individual observer performance, I concluded inter-observer variation was moderate and most observers met Protocol objectives.
- Consequences of observed error in distance estimation for estimation of population density, abundance, and trend likely are small.



A bald eagle surveys Hugh Miller Inlet. (NPS /STEVEN HOEKMAN)

Chapter 3: Species Identification and Abundance Estimation

Abundance estimation is integral to the Protocol but is challenging because murrelets are elusive, cryptic, and inconspicuous; observations relying on fleeting or inconclusive visual cues are inherently imperfect. Protocol abundance estimation relies on line transect surveys (Buckland et al. 2001), which can accommodate incomplete detection (Williams et al. 2002). However, surveys of free-ranging vertebrates typically assume complete and correct species identification. KIMU and MAMU are cryptic species (sympatric with similar morphology and behavior), and misidentification risk is heightened by overlap in habitat use, mixing within social groups, subtle diagnostic characteristics (Figure 9), an unstable survey platform, and challenging weather conditions. Eliminating uncertainty is ideal but likely infeasible. For surveys where these species coexist, 10-40+% partial identification (classification to the lowest certain taxonomic unit, genus *Brachyramphus*) has been common, and misidentification is posited to bias abundance estimates (Kirchhoff 2011, Kuletz et al. 2011a, b, 2013, Hodges and Kirchhoff 2012).

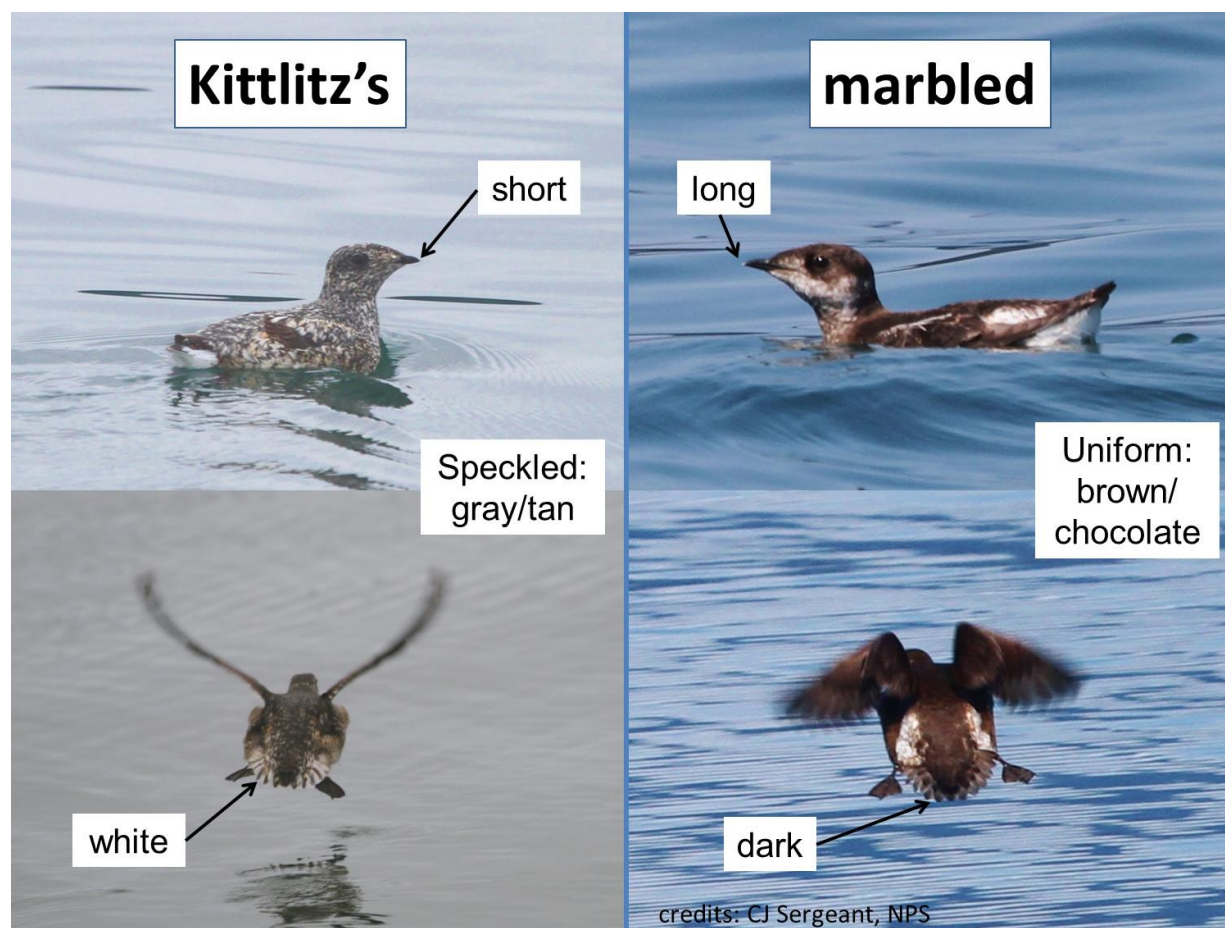


Figure 9. White outer retrices, visible just after taking-off, are diagnostic of the Kittlitz's versus marbled murrelet. Otherwise, identification relies on subtle differences, such as in bill length, feathering at the base of the bill (more pronounced for Kittlitz's), and overall plumage pattern and color. However, morphology varies considerably among individuals. (NPS /CHRIS SERGEANT).

The Protocol attempts to limit potential for misidentification by allowing partial identification when species identity is uncertain. Species-specific abundance is estimated by pro-rating partially-identified individuals using observed species proportions, defined as the proportion of individuals identified as each species. A critical assumption is that observed species proportions are identical to true species proportions, defined as the true proportion of each species in the sample population. This assumption holds if species identification is accurate and probability of partial identification is equal between species. Completely accurate identification likely is unobtainable, but methods are robust to the relaxed assumption of minimal misidentification that is similar between species.

Bias from this approach was unknown, but during Protocol development no superior methods existed. Therefore, the SEAN sought to develop and test novel methods to estimate mis- and partial identification (collectively “uncertain identification”) to assess and improve Protocol performance. Field methods capitalized on high definition digital photography to allow *post-hoc* review of observations, and analytic methods allow estimation of uncertain identification by extending survey observations to additional observers. Here, I 1) describe two field trials testing such methods in GLBA and present summarized results and conclusions, 2) project effects of estimated uncertain identification on Protocol abundance estimates, 3) assess performance of these and related methods, and 4) discuss implications for the Protocol.

2013 Identification Trials

Anne Schaefer (University of Montana), in collaboration with the SEAN, headed a field experiment in GLBA focusing on estimating uncertain identification for observers of varying experience levels. Here, I summarize methods and results presented in Schaefer et al. (2015).

Methods

During 13-18 July 2013, six observers with 0-5 years of experience conducting line transect surveys for these murrelet species participated in boat-based identification trials. As the vessel approached a focal murrelet group (≤ 4 individuals) at ~ 10 km/h, a photographer continuously imaged the group (using a DSLR camera with an 100-400 mm image-stabilized zoom lens) and all observers independently classified individuals as KIMU, MAMU, or partially-identified murrelet (using methods of Kissling et al. 2007, which are similar to this Protocol) every 20-40 m, until contact with the group was lost. Experts positively identified individuals from images.

Generalized linear mixed models were used to estimate mis- and partial identification, with binomial error structure for identification probabilities for individual murrelets. Selection among candidate models using Akaike’s Information Criterion (AIC; Burnham and Anderson 2002) was used to identify best predictive models and covariates, which included observation distance, observer experience, Beaufort force, group size, and group behavior (flushing, diving).

Results and Conclusions

From $\sim 3,000$ observations of 191 murrelet groups, overall estimated misidentification probability was 0.036 ± 0.004 (mean $\pm$ SE). A strong decrease in misidentification with observer experience was the only supported predictive variable (Figure 10). Overall partial identification probability was 0.21 ± 0.01 . Partial identification increased with increasing Beaufort force and observation distance and

decreased with increasing observer experience and with flushing by murrelets. Observers misidentified (0.037 ± 0.010 versus 0.034 ± 0.004) and partially identified (0.22 ± 0.01 versus 0.18 ± 0.01) MAMU slightly more frequently than KIMU.

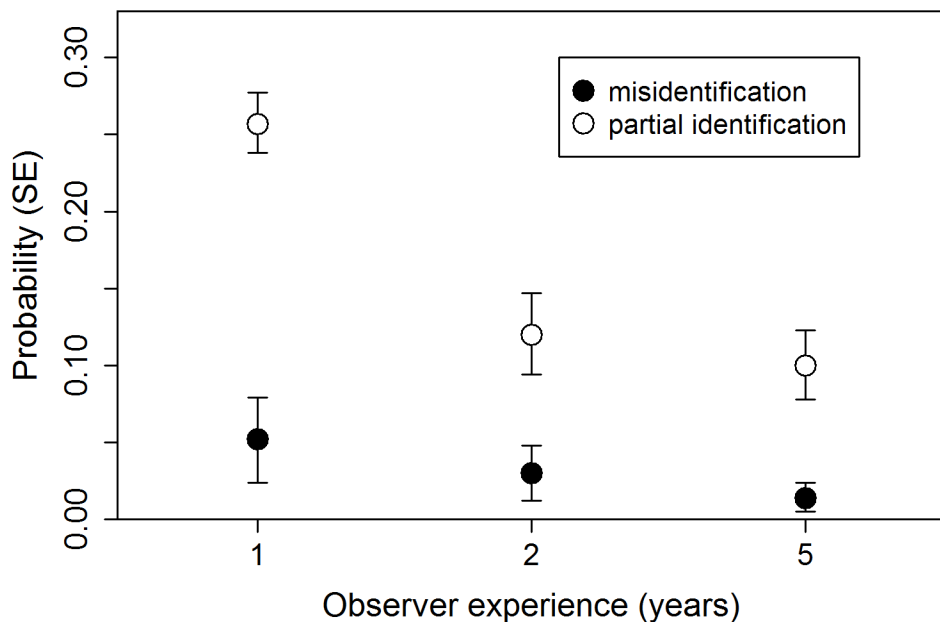


Figure 10. Estimated probability of misidentification and partial identification of Kittlitz's and marbled murrelets during a field experiment in Glacier Bay, AK during July 2013 (modified from Schaefer et al. 2015). Observer experience is number of prior years conducting line transect surveys for these species.

Schaefer et al. speculated that estimated uncertain identification might have been lower than during typical line transect surveys, because of absence of rain and fog and long duration of observations. Additionally, partial identification may have been elevated to avoid misidentification while being “tested.” Using line transect survey data from Icy Bay, AK, Schaefer et al. concluded that effects on species-specific abundance estimates were small. However, they caution that bias could potentially be meaningful, and suggest minimizing uncertain identification by 1) limiting observation distances during surveys and 2) conducting rigorous, standardized training of observers (including feedback and evaluation) before and during surveys.

2014 Identification Trials

In collaboration with the SEAN, I developed novel multi-observation method (MOM) models allowing estimation of uncertain identification and true species proportions and applied these methods during 2014 GLBA surveys. Full methods and results will be published separately.

Methods

In short, MOM models incorporate ≥ 2 observation methods and ≥ 3 observers for surveys of ≥ 2 species. Disagreements in species classifications among observers for the same groups allow estimation of uncertain identification and true species proportions, which are modeled as latent (i.e.,

unobserved) variables. All estimates can vary relative to covariates. Further, complete and accurate observations are not required for any observer.

The SEAN conducted a field trial of MOM sampling during 2014 GLBA surveys. Changes to Protocol survey methods were minimal, primarily consisting of adding a photographer positioned behind survey observers. The photographer used DSLR camera with an 100-400 mm image-stabilized zoom lens to collect still images of a sample of murrelet groups (limited to <10 individuals) classified by survey observers. These groups were subsequently also classified by three “secondary observers” who viewed images on computer monitors. Selection among candidate models using Akaike’s Information Criterion (Burnham and Anderson 2002) was used to identify the best predictive models and covariates (e.g., effects of precipitation and of distance of groups from the transect line on uncertain identification).

Results and Conclusions

In 4 days of sampling on 25 line transects totaling 124 km, the photographer imaged 198 of the 385 murrelet groups recorded by survey observers, obtaining ~3,000 images of 363 individuals. For survey observers with 2 and 3 years of experience, preliminary estimates of misidentification were consistent with predictions (Figure 10, misidentification ~3%, partial identification ~12%) from Schaefer et al. (2015), but substantially higher for partial identification. Uncertain identification for secondary observers was considerably lower, indicating image quality was sufficient to successfully and efficiently apply these methods. For all observers, uncertain identification was similar between species. For both observed species proportions and estimated true species proportions, MAMU exceeded KIMU. Because the relatively common MAMU were more frequently misidentified as KIMU than *vice versa*, observed species proportion for KIMU had substantial positive bias relative to estimated true species proportion. These results strongly imply bias in abundance estimates using current Protocol methods. MOM models can provide reliable estimates when misidentification by survey observers is <15%. However, minimizing uncertain identification, especially misidentification, by primary and secondary observers is critical to precision and reliability of results.

Effects of Uncertain Identification on Protocol Abundance Estimation

Field trials demonstrated pervasive low to moderate misidentification by survey observers, which violated a critical assumption of Protocol statistical methods. Misidentification will bias observed species proportions relative to true species proportions and, given current Protocol methods, will result in nearly identical bias in species-specific abundance estimates.

To better understand implications of uncertain identification across the range of performance for observers of differing experience, I applied estimates from 2013 field trials to project expected bias in estimated KIMU abundance across plausible true species proportions for GLBA, ranging from equal abundance between species to MAMU exceeding KIMU by ~50:1. Critically, these projections do not update prior results, but rather model expectations if posited scenarios *were* true.

When KIMU were relatively common, projected positive bias in KIMU abundance was small and similar among observers of differing experience levels (Figure 11). However, as the true proportion of KIMU decreased, magnitude of positive bias became extreme and increasingly inversely

proportional to observer experience. Misidentification was the dominant source of bias. Relatively common MAMU were more frequently misidentified as KIMU than *vice versa*, resulting in small to large positive bias for KIMU and small negative bias for MAMU.

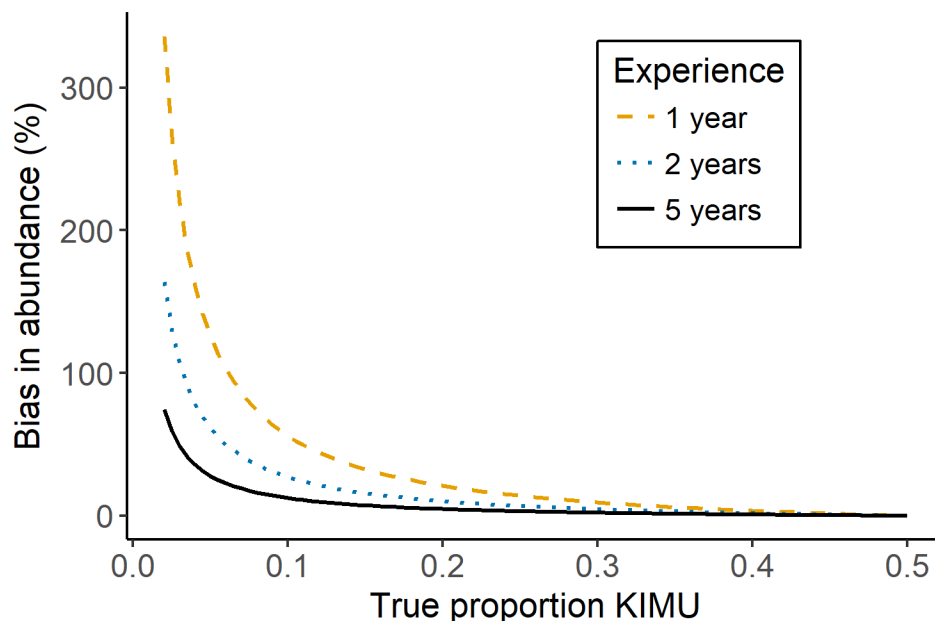


Figure 11. Bias in estimated KIMU abundance relative to true proportion of KIMU in the sample population (bottom x-axis), given estimated uncertain identification from 2013 trials for observers with 1 to 5 years of experience (Schaefer et al. 2015).

Prior Methods for Coping with Uncertain Identification

Abundance estimation is fundamental to ecology, but usually assumes accurate species identification. To avoid risks and cost associated with capture of free-ranging vertebrates, popular methods for estimating abundance rely on enumeration of un-marked individuals and identification from fleeting visual or auditory cues (Buckland et al. 2001, Williams et al. 2002). When identification is uncertain, extensive training is commonly trusted as sufficient to eliminate or minimize misidentification. However, experimental trials using artificial cues have demonstrated pervasive misidentification of 5-10% during multi-species surveys; high levels of experience and training often don't eliminate uncertainty (Simons et al. 2007, McClintock et al. 2010, Campbell and Francis 2011, Miller et al. 2011, 2012, Farmer et al. 2012). Misidentification estimates for murrelets presented here are among the first for free-ranging vertebrates in realistic survey settings. In other field studies, Conn et al. (2013) found ~10% misidentification in aerial line transect surveys for ice-associated seals, and Frare et al. (2017) reported misidentification of >10% for chipmunks.

When risk of misidentification is present, common responses to avert potential bias in abundance estimates have included 1) altering training and survey methods to ensure correct identification or 2) allowing partial identification and then estimating abundance by pooling similar species or by segregating or pro-rating partially-identified individuals (Barlow et al. 2006, Schwarz et al. 2010,

Campbell and Francis 2011, Hoekman et al. 2011c, Piatt et al. 2011). However, these approaches can violate statistical assumptions and provide biased estimates or other ecologically unhelpful information (e.g., pooling rare and common species). Where KIMU and MAMU coexist, Protocol surveys and most similar surveys have applied partial identification (typically 10-40%) and pro-rated to estimate species-specific abundance (Kirchhoff et al. 2010, Kuletz et al. 2011a, b, Piatt et al. 2011); misidentification, although unknown, has been posited to bias abundance estimates (Kirchhoff 2011, Hodges and Kirchhoff 2012, Kuletz et al. 2013).

Assessing Novel Methods for Estimating Uncertain Identification of Murrelets

Field trials demonstrated success of two methods of estimating uncertain identification of free-ranging murrelets *via* images. Estimated misidentification from MOM trials was consistent with predictions of Schaefer et al. (2015); somewhat higher than predicted partial identification may have reflected differences between trials. Schaefer et al. noted absence of precipitation during their trials and longer duration of observations could have depressed partial identification. Observers in MOM trials appeared to avoid substantial additional misidentification in face of poor weather, task saturation, and fatigue during surveys, but at cost of increased partial identification.

Complementary strengths and weakness of these methods, in concert with program goals, outline their potential utilities. Primary benefits of MOM methods are application during surveys, with estimates directly reflecting survey performance, and minimal change to survey methods or increase in field effort. A significant drawback is increased analytic investment and statistical complexity.

Schaefer methods offer more straightforward analyses, can simultaneously assess (and potentially provide feedback to) many observers, can more readily control design elements, and can more easily incorporate covariates. However, Schaefer methods may not directly reflect survey performance (although mimicking survey conditions may mitigate issues), require additional time investment of crew and vessel, and necessitate certain identification of imaged murrelets. Both methods must assume results from small murrelet groups are representative of all groups, as (rare) large groups can't be easily accommodated.

In sum, MOM may be most appropriate for assessing survey performance, while Schaefer methods excel for comparing observers, elucidating factors influencing performance, and potentially as a training tool. Finally, neither method will be a panacea, but rather are useful for assessing uncertain identification and potentially allowing mitigation of its effects if it can't be eliminated.

Implications of Uncertain Identification

Monitoring murrelet abundance in GLBA is a primary Protocol objective. Pervasive low to moderate misidentification, coupled with low true proportion of KIMU, likely have resulted in meaningful positive bias in abundance estimates for KIMU and small negative bias for MAMU. Actual bias is unknown but especially for KIMU likely has varied with annual variation in uncertain identification (e.g., in response to observer experience, environmental conditions) and in true species proportions. Positive bias for KIMU potentially ranges from minimal when misidentification is low and KIMU relatively common to substantial when misidentification is high and KIMU rare. MAMU have predominated in GLBA during 2010-2018 (Table 1.4), and I concluded misidentification is likely the

dominant source of bias in Protocol abundance estimates. Schaefer et al. (2015) concluded that increased observer experience reduced but did not eliminate uncertain identification (Figure 2), suggesting training can limit bias.

Uncertain identification also complicates comparisons among surveys. MAMU have been relatively abundant at many KIMU breeding-season population centers in Alaska. Most surveys have contended with uncertain identification; misidentification, while unknown, likely has biased abundance estimates (Kirchhoff 2011, Kuletz et al. 2011*a, b*, Piatt et al. 2011, Hodges and Kirchhoff 2012). Bias likely differs across space and time, compounding existing impediments to comparison, such as differences in survey design and methods. In GLBA, increased MAMU abundance in 2010-2018 versus 1999-2003 (Table 5) implied heightened bias in KIMU abundance estimates.

Uncertain identification can also bias spatially-explicit density estimates and spatial distributions of populations (Chapter 1). In GLBA, bias likely primarily resulted from misidentification of relatively abundant MAMU. Thus, negative bias for MAMU is likely to be evenly distributed across space, while positive bias for KIMU is likely positively correlated with local MAMU density. Spatially-explicit models estimating species-specific density in concert with uncertain identification are complex, computationally expensive, and data-hungry (Conn et al. 2013).

Conclusions

- Low to moderate species misidentification by survey observers appears pervasive.
- Training and experience likely can reduce, but not eliminate, uncertain identification.
- Species misidentification violates critical assumptions of Protocol statistical methods.
- Uncertain identification and resulting bias in abundance estimates are largely unknown for Protocol surveys, but are likely to differ among years.
- Bias in abundance estimates likely has been small and negative for MAMU and low to substantial and positive for KIMU.
- Potential for positive bias in estimated KIMU abundance is positively related to relative rarity of KIMU and magnitude of misidentification.
- Recent relative rarity of KIMU creates potential for large positive bias in KIMU abundance estimates.
- Misidentification should be minimized to increase reliability of population monitoring.
- Uncertain identification can also bias estimated spatial distributions of populations.
- Nascent methods offer promise for estimating population abundance and spatial distributions while accounting for uncertain identification, but are complex and data-hungry.
- Comparison among murrelet monitoring studies is complicated by differing methods of coping with uncertain identification, differing local true species proportions, and largely unknown but likely differing uncertain identification.



A view of Glacier Bay at South Marble Island. (NPS /BRENDAN MOYNAHAN)

Chapter 4: Detecting Declines in Population Abundance

Statistical power to detect a declining trend in a population's abundance over time ("population decline"), the probability of rejecting a null hypothesis of no decline when it exists, is central to designing and evaluating many monitoring studies for rare species (Gerrodette 1987, Steidl et al. 1997). Prior power analyses indicated plausibility of meeting Protocol objectives of $\geq 80\%$ power to detect a 33% decline of KIMU and MAMU populations over 15 years (Hoekman et al. 2013a). However, limited knowledge of variability in abundance estimates introduced substantial uncertainty (Sims et al. 2007).

Additional uncertainty arose from difficulty distinguishing between these cryptic species. Pervasive uncertain identification (see Chapter 3) violated critical statistical assumptions, likely biasing abundance estimates. In particular, low true species proportion of KIMU creates high potential for misidentification to positively bias abundance estimates. Although uncertain identification is largely unknown for Protocol surveys, I sought to explore implications for estimating population decline, using a range of estimates from GLBA trials to bracket plausible outcomes.

My first objective was to update prior power estimates using current data to estimate variability in abundance estimates. My second objective focused on KIMU; I explored plausible scenarios examining implications of uncertain identification for estimation of population abundance and decline and for power to detect population decline. First, I considered effects of uncertain identification for a population experiencing catastrophic decline. Next, I examined effects of long-term changes in uncertain identification (e.g., from changes in Protocol methods) for a stable population. For both scenarios, I assumed abundant MAMU with stable population growth.

Methods

An appropriate measure of annual variation in population abundance estimates for power analyses is the standard error of estimation (SE.est), estimated as the standard deviation of residuals from a regression of abundance estimates on year (Hatch 2003). The SE.est includes all sources of variation (e.g., sampling error, annual differences in true abundance and in bias in abundance estimates) not attributable to population trend. For each species, I regressed Protocol abundance estimates for 2010-2018 on year and used an (approximately) unbiased estimator of the standard deviation for a normally-distributed variable (Brugger 1969) to estimate

$$\widehat{SE.est} = \sqrt{\frac{1}{n-1.5} \sum_{i=1}^n (x_i - \bar{x})^2}, \quad (2)$$

where n is the sample size of abundance estimates and x_i are residuals from the regression model. I estimated 95% confidence intervals ($\alpha = 0.05$) using critical values of the χ^2 distribution as

$$Pr\left(k \frac{s^2}{\chi_{k,1-\alpha/2}^2} < \widehat{SE.est}^2 < k \frac{s^2}{\chi_{k,\alpha/2}^2}\right) = 1 - \alpha, \quad (3)$$

where k is degrees of freedom for the residuals, s is sample standard deviation, and $1 - \alpha$ is the desired confidence level (Sokal and Rohlf 1995).

Power analyses typically assume dependence between mean abundance and variability in estimates (Gerrodette 1987). This dependence was unknown for these data. As recommended for counts of seabirds, I assumed the coefficient of variation (CV) in abundance estimates was proportional to abundance (Hatch 2003). For each species, I estimated a CV.est and 95% CIs by dividing corresponding values of SE.est by average estimated abundance.

I employed simulations to estimate power to detect population decline for surveys of 5 to 20 years in length where abundance was estimated annually. I projected trend from initial abundance ($N_0 = 10,000$ for KIMU, $N_0 = 70,000$ for MAMU) using an exponential growth model as $N_t = N_0 e^{rt}$, where r is the exponential growth rate and N_0 and N_t are abundance at year 0 and t . I considered the decline defined in the Protocol objective (33% over 15 years, $r = -0.027$, “moderate decline”) and a steeper decline of 50% over 10 years ($r = -0.069$, “catastrophic decline”).

For each of 5,000 simulation replication, I projected population trend and estimated population abundance and trend, either including or excluding uncertain species identification. For simulations excluding uncertain identification, my intent was to update Protocol power analyses with current estimates of variation in abundance estimates. For each species, I simulated annual abundance as

$$\hat{N}_t = N_t + e_t, \quad (4)$$

where e_t was a normal, random variable with a mean of 0 and a standard deviation of $N_t * \text{CV.est}$. I then regressed $\ln(\hat{N}_t)$ on year, with slope coefficients β estimating r , $\beta - r$ estimating bias in r , and the proportion of regressions with a P -value $\leq \alpha$ (0.05) for a one-sided test of negative slope coefficient estimating power to detect population decline. To assess uncertainty in estimated power, I repeated simulations using estimated confidence limits for CV.est.

For simulations including uncertain identification I focused on KIMU, whose rarity increases potential bias in abundance estimates (see Chapter 3). My intent was to project potential for bias in estimates of population abundance and trend and for decreased power to detect population decline.

I assumed Protocol methods were used to classify individuals and pro-rate partially identified individuals to estimate species-specific abundance. Because potential bias in abundance estimates resulting from uncertain identification depends on true species proportions, I partitioned total variance in 2010-2018 abundance estimates for each species into components (using equations 4.2 – 4.4 in Burnham et al. 1987) arising from sampling variance (variance from sampling error) and process variance (here including variance from annual variation in true abundance and in potential bias). I then calculated CV.sampling and CV.est for each species as the square root of the estimated sampling or process variance component divided by average estimated abundance. To highlight potential detrimental effects of uncertain identification when power to detect population decline was adequate, I conducted simulations using the lower 95% confidence limit for CV.est.

To simulate surveys, I used exponential growth models (above) to project trend in abundance at survey year t for KIMU and MAMU (denoted by k and m subscripts). I added annual variation in abundance around the trend as

$$N'_{tk} = N_{tk} + e'_{tk} \text{ and } N'_{tm} = N_{tm} + e'_{tm} \quad (5)$$

where e'_{tk} and e'_{tm} are normal, random variables with a mean of 0 and standard deviation of $N_{tk} * \text{CV.est.k}$ or $N_{tm} * \text{CV.est.m}$ and N'_t is the true abundance for survey year t . Estimated abundance for KIMU included sampling variance as

$$\hat{N}_{tk} = E[\hat{N}_{tk}] + e_{tk}, \quad (6)$$

where e_{tk} is a normal, random variable with a mean of 0 and standard deviation of $N_{tk} * \text{CV.sampling.k}$ and $E[\hat{N}_{tk}]$ is the expected estimated abundance calculated as

$$E[\hat{N}_{tk}] = \frac{N'_{tk} \cdot \text{Pr}\{\text{identification}\} + N'_{tm} \cdot \text{Pr}\{\text{misidentification}\}}{(N'_{tk} + N'_{tm}) * (1 - \text{Pr}\{\text{partial identification}\})} \cdot (N'_{tk} + N'_{tm}), \quad (7)$$

where $\text{Pr}\{\text{identification}\} = 1 - \text{Pr}\{\text{misidentification}\} - \text{Pr}\{\text{partial identification}\}$ and uncertain identification is assumed equal between species.

In the first set of simulation scenarios, I examined potential effects of uncertain identification on initial population of 5,000 KIMU experiencing catastrophic decline; an initial population of 70,000 MAMU had a stable trend ($r = 0$). To capture reasonable extremes in uncertain identification by survey observers, I conducted simulations using estimates from Schaefer et al. (2015) for observers with 1 or 5 years of experience (Fig 2). I also considered a scenario where uncertain identification varied annually, following a uniform, random distribution between estimates for observers with 1 and 5 years of experience. I assumed perfect correlation between mis- and partial identification. To assist visualizing potential bias in abundance estimates resulting from uncertain identification, I also projected expected abundance estimates for surveys with observers with 1 or 5 years of experience for an initial KIMU population of 10,000 experiencing catastrophic decline.

In a second scenario, I examined potential effects of dramatic reduction in uncertain identification for a stable populations ($r = 0$) of KIMU ($N_0 = 5,000$) and MAMU ($N_0 = 70,000$). I used estimates of uncertain identification for observers with 1 year of experience until a “change point” at year 7, and thereafter used estimates for observers with 5 years of experience. I conducted all analyses using the R statistical computing environment version 3.3.1 (R Core Team 2019).

Results

Estimated CV.est for KIMU (0.30, 95% CI = 0.20 – 0.61) slightly exceeded that for MAMU (0.22, CI = 0.15 – 0.46). Large uncertainty in CV.est and resulting estimates of power to detect population decline (Figure 12, 13) reflected limited sample size ($n = 9$). Power to detect a moderate decline was low, and CIs for KIMU did not overlap Protocol objectives of 80% power at 15 years. Mean power to detect a catastrophic decline was high at 15 years, although uncertainty was high.

Estimated CV.sampling for KIMU (0.20) and MAMU (0.15) indicated that sampling error accounted for ~45% of annual variation among abundance estimates. Projections for a catastrophically declining KIMU population indicated uncertain identification created substantive positive bias in abundance estimates (Figure 14). Bias was inversely related to observer experience and true abundance.

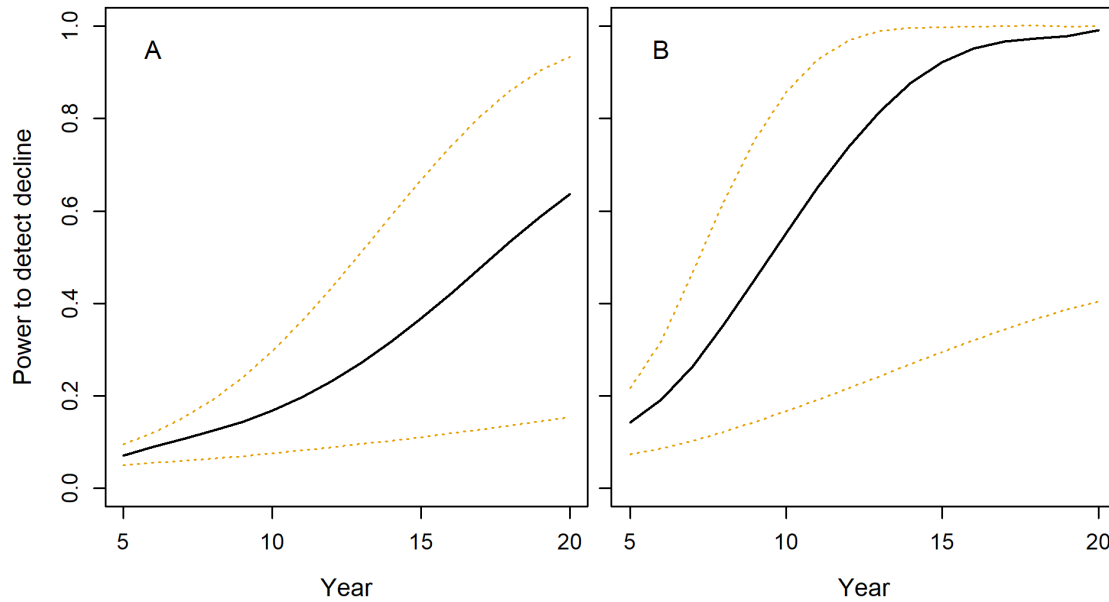


Figure 12. Estimated power (solid line) and 95% confidence limits (dotted lines) to detect a moderate (A, $r = -0.027$) or catastrophic population decline (B, $r = -0.069$) of Kittlitz's murrelets in Glacier Bay, AK. Uncertainty in estimated power reflected uncertainty in predictions of annual variation in abundance estimates around the population trend.

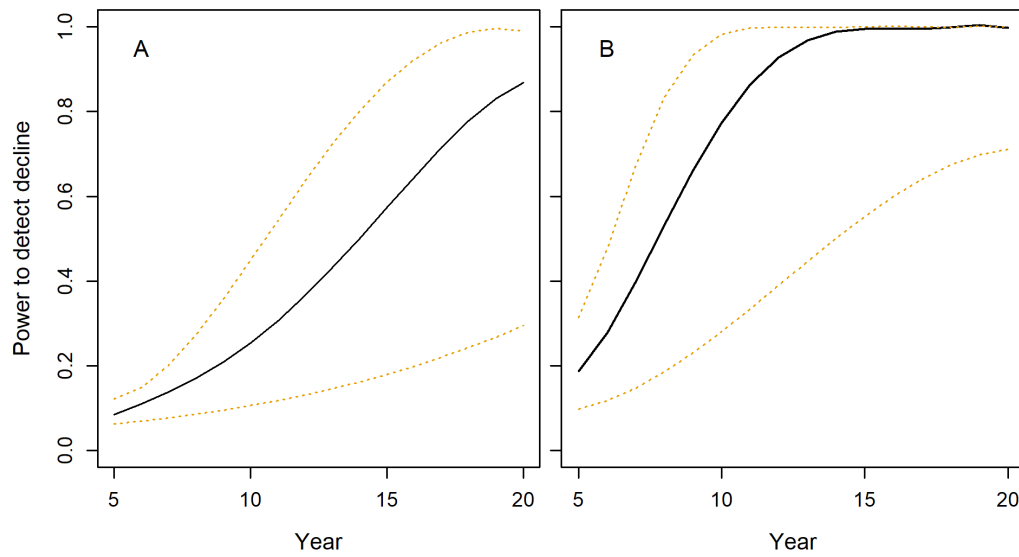


Figure 13. Estimated power (solid line) and 95% confidence limits (dotted lines) to detect a moderate (A, $r = -0.027$) or catastrophic population decline (B, $r = -0.069$) of marbled murrelets in Glacier Bay, AK. Uncertainty in estimated power reflected uncertainty in predictions of annual variation in abundance estimates around the population trend.

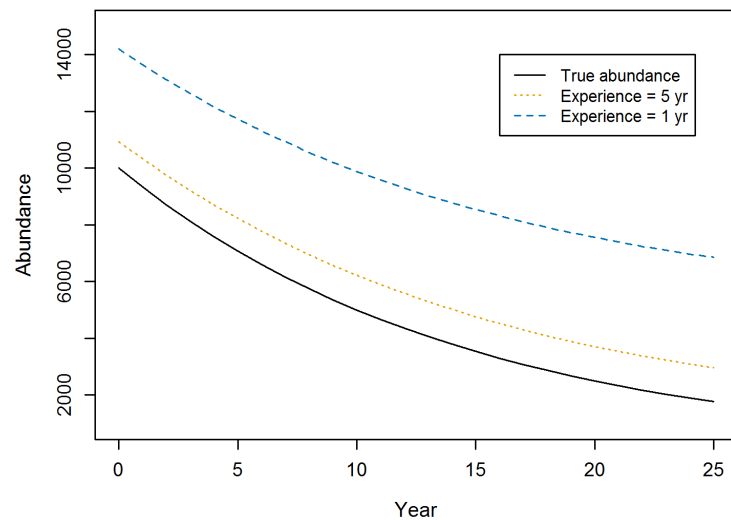


Figure 14. Projected true abundance (solid line) for an initial population of 10,000 Kittlitz's murrelets experiencing catastrophic population decline ($r = -0.069$) and expected abundance estimates from surveys with uncertain identification for observers with 1 (dashed line) or 5 (dotted line) years of experience (Schaefer et al. 2015). Simulations assumed a stable population of 70,000 marbled murrelets and abundance estimation using current Protocol methods.

For a scenario of KIMU populations experiencing catastrophic decline, consistent uncertain identification resulted in consistent positive bias in abundance estimates that modestly reduced power to detect population decline (Figure 15), but estimated declines were smaller than true declines. However, random annual variation in uncertain identification increased annual variation in bias and in abundance estimates, resulting in moderate to large decreases in power. Positive bias in estimated abundance and population trend was most severe when uncertain identification was high (Figure 16). Increasing bias in abundance estimates with decreasing true abundance amplified both reductions in power and positive bias population trend.

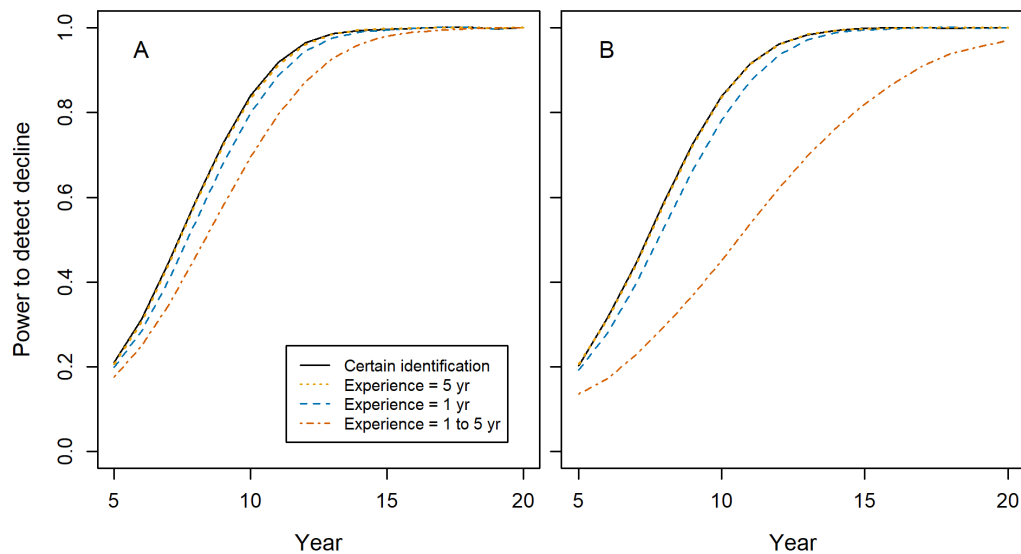


Figure 15. Estimated power to detect a population of Kittlitz's murrelets in Glacier Bay, AK experiencing catastrophic decline ($r = -0.069$) from an initial population of A) 10,000 or B) 5,000. Lines reflect certain identification (solid line), uncertain identification (Schaefer et al. 2015) for observers with 1 or 5 years of experience (dotted and dashed lines), and random annual variation in uncertain identification (dot-dash line). Simulations assumed a stable population of 70,000 marbled murrelets and abundance estimation using current Protocol methods.

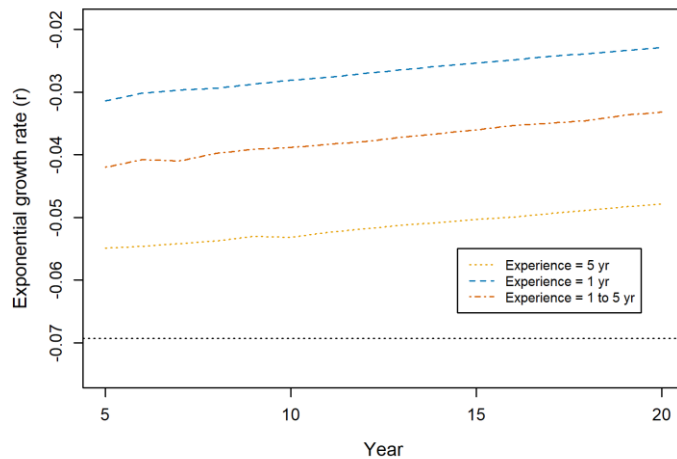


Figure 16. Mean estimated exponential growth rate for a population of Kittlitz's murrelets in Glacier Bay, AK experiencing catastrophic decline ($r = -0.069$; dotted, black line) from an initial population of 5,000. Lines reflect estimated uncertain identification (Schaefer et al. 2015) for observers with 1 or 5 years of experience (dotted and dashed lines) and random annual variation in uncertain identification (dot-dash line). Simulations assumed a stable population of 70,000 marbled murrelets and abundance estimation using current Protocol methods.

A sharp reduction in uncertain identification caused elevated Type I error for detecting population decline (Figure 17A) and substantial negative bias in estimated population trend (Figure 17B), as reductions in uncertain identification reduced positive bias in abundance estimates.

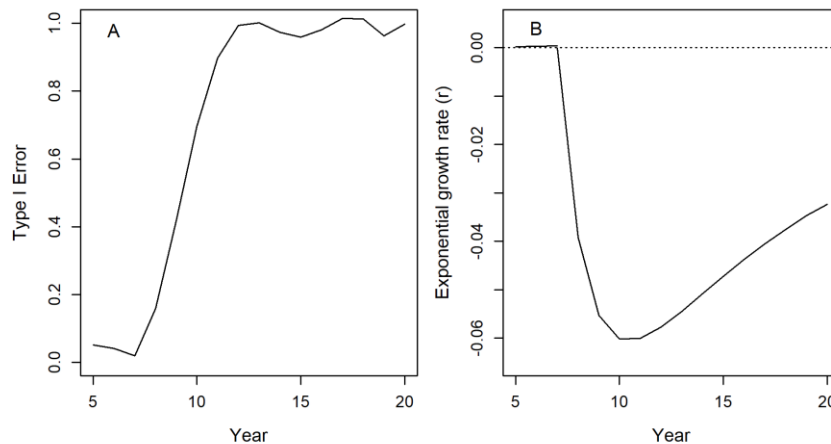


Figure 17. Solid lines show estimated Type I error for detecting population decline (A) and estimated exponential growth rate (B) for a stable population ($r = 0$, dotted line) of Kittlitz's murrelets in Glacier Bay, AK with an initial population of 5,000. At survey year 8, uncertain identification declined from that estimated for survey observers with 1 year of experience to 5 years of experience (Schaefer et al. 2015). Simulations assumed a stable population of 70,000 marbled murrelets and abundance estimation using current Protocol methods.

Discussion

Statistical power analyses for detecting population decline typically assume unbiased abundance estimates, but uncertain identification can bias abundance estimates, especially for rare populations. Biased abundance estimates can bias estimated population trend and increase variation in abundance estimates, which is strongly inversely related to power to detect population trend (Larsen et al. 2001, Sims et al. 2007). For both murrelet species, high annual variation in 2010-2018 abundance estimates suggested lower than desired power to detect population declines. However, high uncertainty about the source of annual variation and in projecting its future magnitude precluded firm conclusions. Annual variation in abundance estimates reported here exceeded that used during Protocol planning (KIMU CV = 0.30 here versus 0.20, MAMU CV = 0.22 here versus 0.14; Hoekman et al. 2013). Higher than projected sampling error contributed to this increase, but a combination of variation in true abundance and any bias in estimates accounted for >50% of annual variation in abundance estimates. The perhaps only viable remedy for high true variation is accumulating additional survey years (Larsen et al. 2001). High annual variation in abundance estimates has been typical for murrelets in GLBA (e.g., CV = 0.32 for KIMU during 1999-2003 from Piatt et al. 2011) and elsewhere. Potential explanatory factors include: variability in breeding effort and success, regional movements in response to breeding habitat conditions, movement of non-breeding or post-breeding birds, and variation in uncertain identification (Peery et al. 2004, Kirchhoff 2008, 2011, Hodges and Kirchhoff 2012, Bertram et al. 2015, 2016, Kissling et al. 2015a, b, 2016).

The magnitude and sources of bias in abundance estimates were unknown. However, I found observed variation in uncertain detection by survey observers could strongly reduce power to detect KIMU decline. Across many studies, experience and individual characteristics have strongly influenced observer performance, likely increasing variation in abundance estimates and decreasing power to detect population trend (Alldredge et al. 2007, Farmer et al. 2012, 2014, Miller et al. 2012, Nolte et al. 2016, this study). Additional to substantial variation in observer experience (Table 1), potential effects of large differences in environmental conditions across years were unknown (Table 2). Finally, magnitude of bias in abundance estimates from uncertain depends in part on true species proportions; large annual variation in true abundance of both species could also contribute to variation in bias. I hypothesized that annual variation in bias arising from uncertain identification has substantively contributed to variability of abundance estimates.

Non-random variation in bias among annual abundance estimates likely will bias estimated population trend. Bias in abundance estimates arising from misidentification is particularly troublesome for rare species, because potential positive bias in abundance is inversely related to low true species proportions (see Chapter 3). Decline produces escalating positive bias in estimated abundance and population trend, potentially masking catastrophic decline. Simulations projected substantive under-estimation of catastrophic decline for KIMU even with experienced observers and severe bias in trend (<50% true values) with inexperienced observers. In general, bias in estimated population trend was sensitive to magnitude of misidentification, while decline in power to detect decline was sensitive to annual variation in misidentification.

Non-random variation in uncertain identification over time could also bias trend estimates. Improvement in performance as survey observers accrue experience, as well as individual differences in performance, can introduce spurious trends in population data (Sauer et al. 1994, Farmer et al. 2014, Nolte et al. 2016). GLBA murrelet surveys rely on a small number of observers who often return for a series of years. Trends or abrupt changes in uncertain identification could result from individuals accruing experience, introduction of inexperienced observers, altered training methods, and individual traits. Simulation results indicated long-lasting change in uncertain identification could lead to spurious detection of population trend, suggesting circumspection when modifying Protocol methods (e.g., survey observer training, field methods) potentially altering uncertain identification. In all scenarios, minimizing uncertain identification, and in particular misidentification, was paramount to increasing reliability of monitoring results, while low true species proportions exacerbated problems. If misidentification could be minimized in future surveys, reliable estimation of population trend would likely require effective modeling uncertain identification and its effects on abundance estimates.

For a rare species at risk of uncertain identification with an abundant species, reliably detecting population decline will likely necessitate mitigating potential bias in estimates of population abundance and trend. In GLBA, relative rarity of KIMU in combination with uncertain identification creates significant, but currently poorly understood, risk of incorrect conclusions from monitoring using current Protocol methods. Chapter 5 discusses alternatives for assessing and averting this risk.

Conclusions

Here I summarize conclusions for KIMU, because inference about the focal Protocol species is likely to be more strongly impacted by uncertain identification.

- High variation in annual abundance estimates suggests lower than desired statistical power to detect population decline.
- Even modest misidentification has high potential to reduce statistical power to detect population decline and to positively bias estimates of population abundance and trend.
- Population decline will likely increase positive bias in abundance estimates from misidentification, potentially masking catastrophic decline.
- Magnitude of misidentification drove potential bias in estimation of population trend, while annual variation in misidentification drove reduction in power to detect population decline.
- Reliably detecting population decline will likely necessitate mitigating risks from misidentification by minimizing and/or statistically controlling for it.
- Minimizing misidentification without effectively accounting for it in prior surveys may create spurious evidence for population decline.



Flukes of a diving humpback whale. (NPS /BRENDAN MOYNAHAN)

Chapter 5: Summary and Recommendations

Conclusions

Salient conclusions and accompanying implications for the Protocol from all chapters are summarized by topic.

Population Abundance

- Dense concentrations of KIMU (mean ~10,000) and MAMU (~63,000) in GLBA during early July constitute a significant fraction of global populations for both species.
- Differences in methods introduced substantial uncertainty in comparing abundance estimates among surveys from different times and regions.
- Protocol breeding season abundance estimates during 2010-2018 have increased (KIMU ~125%, MAMU ~500%) relative to estimates from strip transects during 1999-2008, but extent of differences explained by methodological differences is uncertain.

Population Spatial Distributions

- Densities of MAMU survey observations increased with proximity to the mouth of GLBA.
- KIMU survey observations have been concentrated in a few hotspots distributed across GLBA, with consistent moderate densities in upper fjords.

Distance Estimation Calibration

- Survey observers met Protocol goals for proficiency in distance estimation, and projected effects of estimation error on estimates of population abundance and trend appeared minimal.

Uncertain Species Identification

- Field trials validated two alternative methods for estimating uncertain identification of free-ranging murrelets *via* digital photography and additional observers.
- Low to moderate misidentification and high partial identification appeared pervasive among survey observers.
- Experience and training likely can reduce, but not eliminate, uncertain identification.

Estimating Population Abundance

- Critical assumptions of Protocol methods for abundance estimation (primarily, no misidentification) were unsupported, likely biasing estimates of population abundance and spatial distribution.
- Uncertain identification and bias in estimated abundance were largely unknown. Potential bias increases with magnitude of misidentification and low true species proportion, and even low misidentification can introduce substantive positive bias to estimated KIMU abundance.
- Nascent methods for estimating population abundance and spatial distribution accounting for uncertain identification are complex, data-hungry, and most effective when uncertain identification is low.

- Comparison of abundance and spatial distribution across space and time are complicated by likely differences in uncertain identification and associated bias.

Detecting and Estimating Population Decline

- High annual variation in abundance estimates suggested lower than desired statistical power to detect population declines, but conclusions were uncertain.
- For declining populations, misidentification has high potential to reduce statistical power to detect decline and to positively bias estimates of population trend.
- For KIMU, catastrophic population decline could be masked by escalating positive bias in estimated abundance arising from infrequent misidentification.
- Minimizing misidentification and mitigating its effects are paramount to increasing statistical power to detect population declines and reliability of monitoring results.

Potential Enhancements to Protocol

Specific recommended enhancements to the Protocol are organized by topic. Substantive changes should be implemented as specified in SOP 10: Protocol Revision (Hoekman et al. 2013a).

Survey Operations

- Update methods for data acquisition and management and for production and dissemination of deliverables to reflect transition from NPTransect to Park Observer software for acquisition of survey data. Add data fields to associate individual survey observers with each observation record. Keep records of survey experience of each year's observers.
- Sampling of a transect should be completed before or initiated after cruise ships are within ≥ 2.5 km of the transect.

Distance Estimation Calibration

- Seek to increase training and assessment during challenging environmental conditions (e.g., fog and Beaufort force 2) to improve and better understand performance.
- Seek to increase training and calibration for targets at 125-200 m and explore methods of enhancing capability to acquire targets with laser rangefinders at these distances.

Uncertain Species Identification

Uncertain identification by survey observers appears pervasive and unavoidable, but even low levels of misidentification can potentially undermine reliability of monitoring. Options for mitigation span diverse field and analytic methods, including:

- Minimizing uncertain identification, especially misidentification, by survey observers.
- Assessing uncertain identification by survey observers under realistic field conditions.
- Statistical modeling of uncertain identification to minimize potential bias in estimates of population abundance and spatial distribution.

Where possible, I present complementary alternatives reflecting a range of resource investments.

Minimizing Uncertain Identification

Minimizing misidentification by survey observers is paramount to increasing reliability of results, both by reducing potential bias in abundance estimates and by increasing precision and reliability of statistical models estimating misidentification. Allowing partial identification may help minimize misidentification, but all else equal, minimizing partial identification is also beneficial. Challenges to identification arise from wet and fogged binoculars, an unstable vessel with increasing wave height, task-saturation limiting attention to identification (especially by limiting opportunity to identify birds as they flush), and long observation distances. These might be mitigated by sheltering observers from precipitation, binoculars with image-stabilization and water-beading nano-coated optics, and an additional observer dedicated to species identification. Limiting observation distances far from the transect line (complete detection near the line is required) may reduce misidentification, but benefits must be balanced against reduced samples for estimation of encounter rates and detection probability. Ideally, skilled observers should be cultivated by increasing quantity and quality (by providing feedback and performance assessment *via* digital images) of standardized training and, when possible, be retained across years. Given constraints on vessel and crew time, supplementing on-water training with training *via* images and video may be most feasible.

Assessing Uncertain Identification

Assessment of uncertain identification can maximize benefits of training, assure adequate performance, and provide data for statistical modeling. A feedback loop where observers are regularly assessed, with performance goals allowing for imperfection and improvement over time, would facilitate improvement and avoid over- and under-confidence.

Ideally, performance would be assessed during surveys or similar conditions. Identification trials (see Chapter 3) in 2013 (“Schaefer methods”) and 2014 (multi-observation method or “MOM”) provide templates for potential identification assessment as part of annual operations. Schaefer methods, perhaps modified to mimic duration and distance of survey observations, could provide immediate feedback, but would require additional effort by the crew and vessel. Concentrating assessment early in survey operations might aid training. Alternatively, adding a photographer to apply MOM methods would allow assessment during surveys, but without immediate feedback. Large samples would benefit both alternatives. At best (a binomial model with no overdispersion or predictive variables), a standard error of 0.01 for estimated misidentification probabilities of 0.01 or 0.05 would require samples of ~100 or ~500 identification trials. In practice, Schaefer methods generated a sample of ~350 (each identified by ~4 observers) over 6 days. Over 4 days, MOM sampling generated a sample of ~350 (~50% of observed murrelets), suggesting a maximum of ~1,250-2,000 trials during annual surveys. Realistic expectations might be providing feedback to observers, an assessment of overall performance each year, and possibly contributing to statistical modeling (below). Less formal methods providing performance feedback (for example, on-water identification in tandem with digital photography or using computer-based images and video) could efficiently aid training and assessment, especially for inexperienced observers.

Statistical Modeling of Uncertain Identification

Statistical methods accounting for uncertain identification when estimating population abundance and spatial distribution can minimize potential bias (Conn et al. 2013, 2014, Sollmann et al. 2016) which will increase with higher misidentification and relative rarity of populations. Ideally, methods assessing uncertain identification should closely mimic survey conditions and model important sources of heterogeneity in data *via* explanatory variables. However, sufficient precision will require large sampling effort. For ecological monitoring, Ruiz-Gutierrez et al. (2016) recommended samples of 5,000 or 15,000 independent, identified individuals for expected misidentification of 1% or 5%.

Adequate samples could be accrued from identification assessment conducted annually as part of survey operations (above); Schaefer versus MOM methods each include potential caveats (see Chapter 3). These assessments would reflect only observers and conditions present during surveys. Data pooled across years would suffer from design issues – e.g., unbalanced samples among factor levels, confounding of predictors, and poor coverage across the range of covariate values – causing estimation problems. Alternatively, Schaefer methods offer opportunity for field experiments independent of annual surveys, where researchers could more easily control covariates (e.g., include observers with diverse experience levels) and seek balanced samples across factor levels. Other potential advantages include maximizing efficiency by simultaneously assessing many observers, avoiding lengthening annual surveys, and potentially augmenting assessment data collected during survey operations. Potential caveats include that performance may not be representative of surveys because of differences in methods or observers and the substantial time investment for the vessel and observers.

Models of uncertain identification could be applied to estimate uncertain identification for each survey year based on important predictive variables. Although enhancing Protocol methods to reduce misidentification would be beneficial, a potential complication would be accounting for largely unknown, but potentially higher, misidentification during prior years. Failure to account for this discrepancy could positively bias prior abundance estimates and increase probability of falsely detecting KIMU population decline (Chapter 4). A potential remedy could be estimating effects of altered methods on misidentification, for example using pre- and post-training assessment.

Low true species proportions for KIMU heightened sensitivity of their estimated abundance to misidentification. Inaccuracy in abundance estimates resulting from inaccuracy in estimated uncertain identification will be magnified by increasing relative rarity. Disparate spatial distributions between species (Figure 3, 4) offer opportunity to minimize estimation issues, for example by estimating KIMU abundance excluding areas where MAMU are abundant and KIMU rare.

Evaluating Alternative Approaches

A successful approach will combine one or more elements above to estimate population abundance with minimal bias and sufficient precision. Reducing uncertain identification, particularly misidentification, is paramount. However, given low true species proportions for KIMU, reduction in misidentification alone will be unlikely to adequately limit bias in estimated abundance when misidentification exceeds minimal levels (i.e., >1-2%), and consequences of failing to account for uncertain identification will increase rapidly with higher misidentification.

Viable approaches to estimating uncertain identification include: integrating a photographer into survey operations to conduct MOM sampling (adding 1 person to annual surveys with no change in duration), integrating Schaefer methods into survey operations (adding ~1-2 days to duration of annual surveys), and applying Schaefer methods as ≥ 1 independent, designed experiments (weeks of effort for a vessel and large crew). All alternatives would require substantial effort for data processing and analyses. Analyses of expected precision of estimates relative to sample size would be essential to projecting resource investments and benefits of each alternative.

Emphasis of Future Periodic Review

Assuming the Protocol incorporates methods for estimating uncertain identification, I suggest the next periodic review split effort between 1) assessing uncertain identification methods and results and 2) applying estimates of uncertain identification to estimate population abundance, spatial distributions, and trend. Objectives (in decreasing priority) may include:

- Assess uncertain identification: Assess survey observer training and performance, estimate uncertain identification and effects of predictive variables.
- Assess detection functions: Analyze effects of predictors, such as weather conditions, on detection probabilities, and use appropriate methods to assess potential differences between species (accounting for uncertain identification).
- Estimate population abundance: Estimate annual species-specific population abundance applying appropriate models of detection probability and uncertain identification.
- Estimate spatial distribution of populations: Estimate spatially-explicit, species-specific population densities appropriately accounting for uncertain misidentification.
- Estimate population trend: estimate species-specific population trend using best-available estimates of population abundance.



A Kittlitz's murrelet leaves a trail of wingtip vortices on calm water. (NPS /STEVEN HOEKMAN)

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