Tools and Technology

Testing Methods for Using High-Resolution Satellite Imagery to Monitor Polar Bear Abundance and Distribution

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ABSTRACT High-resolution satellite imagery is a promising tool for providing coarse information about polar species abundance and distribution, but current applications are limited. With polar bears (*Ursus maritimus*), the technique has only proven effective on landscapes with little topographic relief that are devoid of snow and ice, and time-consuming manual review of imagery is required to identify bears. Here, we evaluated mechanisms to further develop methods for satellite imagery by examining data from Rowley Island, Canada. We attempted to automate and expedite detection via a supervised spectral classification and image differencing to expedite image review. We also assessed what proportion of a region should be sampled to obtain reliable estimates of density and abundance. Although the spectral signature of polar bears differed from nontarget objects, these differences were insufficient to yield useful results via a supervised classification process. Conversely, automated image differencing—or subtracting one image from another—correctly identified nearly 90% of polar bear locations. This technique, however, also yielded false positives, suggesting that manual review will still be required to confirm polar bear locations. On Rowley Island, bear distribution approximated a Poisson distribution across a range of plot sizes, and resampling suggests that sampling >50% of the site facilitates reliable estimation of density (CV <15%). Satellite imagery may be an effective monitoring tool in certain areas, but large-scale applications remain limited because of the challenges in automation and the limited environments in which the method can be effectively applied. Improvements in resolution may expand opportunities for its future uses.

KEY WORDS abundance estimation, Arctic, marine mammal, polar bear, remote sensing, resampling, satellite imagery, *Ursus maritimus*.

Recent advances in remote sensing technologies and detection methods are providing new opportunities for estimating wildlife abundances and distributions. In particular, researchers are turning to very high resolution (i.e., VHR; 0.5–5.0-m pixel size) satellite imagery to assess populations and the impacts of a changing climate, primarily in the polar regions (e.g., LaRue et al. 2011, 2013; Fretwell et al. 2012; Lynch and LaRue 2014; Stapleton et al. 2014*a*). By providing remote access to study sites and eliminating concerns about human safety and wildlife disturbance, satellite imagery can yield data on wildlife abundance and distribution and thus may be integrated into larger scale monitoring programs.

The polar bear (*Ursus maritimus*) is one species for which researchers have examined the feasibility of satellite imagery as a monitoring tool (Stapleton et al. 2014*a*). Physical mark–recapture has been the primary technique used to inventory polar bear populations in North America for decades (e.g., DeMaster et al. 1980, Lunn et al. 1997, Regehr et al. 2007, Stirling et al. 2011). Despite intensive public interest, the bear's cultural importance to northern communities, and its status as a symbol of climate change (Slocum 2004, O'Neill et al. 2008), data on abundance, status, and trends are lacking for many populations (IUCN/PBSG 2014), necessitating the development of a global monitoring framework (Vongraven et al. 2012). These gaps in knowledge are the result of several factors, including the costs and significant logistical challenges of implementing capture-based population studies in remote parts of the Arctic. This reality, coupled with the recognition that research techniques can

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better integrate cultural values of Arctic residents by reducing capture and handling (Peacock et al. 2011), has compelled many jurisdictions to invest significant resources in alternative inventory methods, including aerial surveys and remote sensing (Stapleton et al. 2014*b*).

The first test of the feasibility of satellite imagery as a monitoring method for polar bears was performed by Stapleton et al. (2014*a*) on small islands in northern Foxe Basin, Nunavut, Canada, during the ice-free season in the late summer of 2012. This work indicated that polar bears can be reliably identified and distinguished from similarly sized objects (e.g., rocks) in snow-free sites with minimal topographic relief by using multiple VHR panchromatic (i.e., black and white) images (Stapleton et al. 2014*a*). An estimate of abundance derived from satellite imagery counts was highly consistent with an estimate based on established aerial survey techniques. The major drawback to the technique, however, was the amount of time it took to manually review images (100 hr to review approx. 1,100 km^2). This alone could preclude large-scale application of the technique; so, though VHR imagery has demonstrated promise for remote-monitoring of polar bears, there is still a need for expediting the process.

In addition, technical analyses of imagery can be hampered by a suite of environmental factors, such as shadows because of low sun angles, extensive rubble, cloud cover, patchy snow, and small ice floes washed ashore. These factors may inhibit or altogether preclude reliable detection at sites with moderate to high topographic relief or when imagery is collected at an inopportune time (M. LaRue and S. Stapleton, unpublished data). Obtaining suitable imagery from a broad geographic area during a narrow temporal window may not always be logistically feasible (e.g., clouds can prevent successful image collection for extended periods). Collection of large volumes of imagery also may prove cost-prohibitive depending on collection factors such as use of panchromatic versus multispectral imagery, or spatial and spectral resolution.

In this study, we evaluated opportunities for expanding large-scale applications of satellite imagery. To accomplish this objective, we re-examined polar bear locations identified in Stapleton et al. (2014*a*) and the associated satellite imagery. We attempted to expedite image review by automating detection of polar bears via open-source platforms and traditional remote-sensing methods (i.e., classification with spectral reflectances and image differencing). We conducted resampling simulations of these location data to evaluate whether sampling significantly smaller proportions of a site could yield reliable estimates of density and abundance, thereby reducing logistical challenges and resources required for collecting and reviewing imagery.

STUDY AREA

The Foxe Basin polar bear population, located in Nunavut and Quebec, Canada, covers approximately 1.1 million km^2. Initial field work described in Stapleton et al. (2014*b*) was conducted on Rowley Island (approx. 1,000 km^2, located at 69°N, 78°W) in northern Foxe Basin. The island's snow-free landscape, minimal topographic relief, and high concentrations of bears provided an ideal setting for evaluating and developing remote-sensing methods (Stapleton et al. 2014*a*).

METHODS

Automating Detection

Our first goal was to explore multiple options for automating —and thus expediting—image review and detection of polar bears using VHR images. We examined 2 primary methods to determine the feasibility of automation: 1) analysis of, and reclassification with, percent reflectances; and 2) image differencing or change detection. In this attempt at automation, we intentionally used software with which most researchers are familiar or have access (ArcGIS 10.2; Esri, Redlands, CA). Although we recognize the power and utility of remote-sensing programs such as ENVI (Envivio, Inc., San Francisco, CA) or ERDAS (Hexagon Geospatial, Norcross, GA), our intention was to build an easily reproducible method for use by wildlife biologists and managers, and not necessarily for use by experts in remote sensing.

Percent reflectances.—We explored the idea of using the reflectance values of polar bears on imagery to automate detection. Reflectance values represent the amount of light returning from an object to the satellite sensor (Martonchik et al. 2000). Objects on the landscape have different reflectance values (e.g., bare ground has a lower reflectance value than ice or snow), and we hypothesized that although polar bears and nontarget objects on the landscape such as rocks, foam, and remnant ice floes are very similar in coloration, polar bears would have a lower reflectance value than these nontargets on panchromatic imagery. We did not use multispectral imagery because of resolution constraints (Fig. 1; see Discussion). We loaded images into ArcGIS 10.2 and extracted the reflectance values from pixel clusters of a sample of presumed bears ($n = 90$) identified in Stapleton et al. (2014*a*) as well as samples of nontarget objects ($n = 67$; see Stapleton et al. 2014*a* for discussion on ground validation to ensure that our manual review and differentiation of items on the landscape was accurate). We calculated average reflectance values and standard deviations for presumed bears and nontargets. We used the polar bear mean reflectance value (± 2 SDs) to reclassify image mosaics. This process enabled us to separate a "polar bear" class from the remaining landscape features of Rowley Island. We then converted the reclassified raster image to a vector format, extracted and calculated areas of "polar bear" polygons, and selected "polar bear" polygons that were 2.0–4.0 m^2—this is the area taken up by a subadult or adult polar bear (Stapleton et al. 2014*a*). We overlaid the resultant polygons on Rowley Island and determined the number of presumed polar bears that were covered by the reflectance-based polygons.

Image differencing.—Image differencing, also known as change detection, identifies differences between remotely sensed images collected at different times (Singh 1989, Lu et al. 2004) and is commonly used for determining

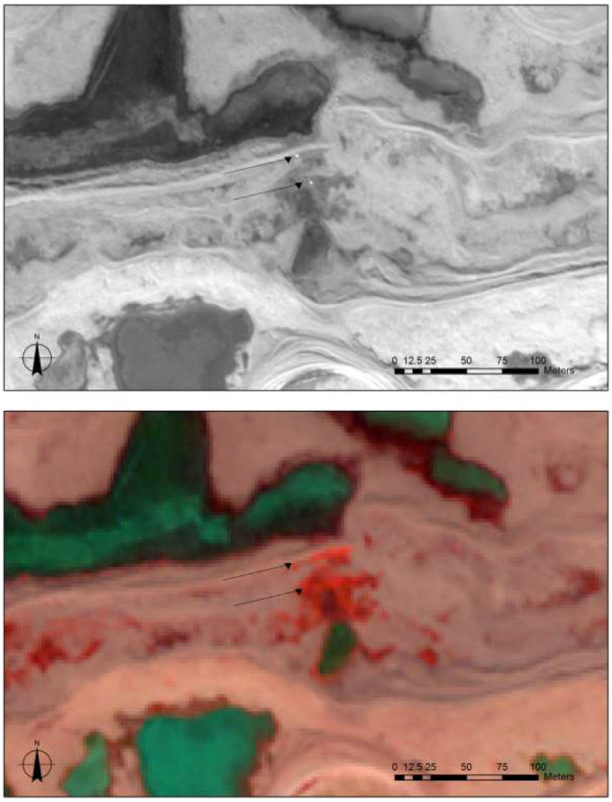

Figure 1. Example of polar bears on panchromatic imagery (top image; 0.6-m resolution) and multispectral imagery (bottom image 2.4 m resolution).

environmental change (e.g., land use–land-cover change [Gautam and Chennaiah 1985, Weng 2002]; deforestation [Moran et al. 1994, Hudak and Wessman 2000, Alves 2002]; detecting fire [Wessman et al. 1997, Cuomo et al. 2001]; and monitoring drought, floods [Jacobberger-Jellison 1994, Liu et al. 2002], and marine environments [Michalek et al. 1993]). Previous work by Stapleton et al. (2014*a*) used a manual form of image differencing to identify polar bears: they were the small, white objects present on the image of interest (i.e., target image) but not on the comparative image (i.e., reference image). We hypothesized that on the relatively barren landscapes of the Arctic, automated image differencing could provide an effective means of reviewing imagery collected during the ice-free season.

To evaluate automated image differencing, we used target and reference satellite imagery from Rowley Island (Stapleton et al. 2014*a*) and subtracted the reference images from target images using Map Algebra within ArcGIS 10.2. The resulting raster calculation highlighted pixels that were present on one image and absent on the other (where the images overlap). We then overlaid the locations of presumed polar bears (Stapleton et al. 2014*a*) to calculate the number of bears that were identified as being "different"—present on the target images but absent on the reference images.

Evaluating Sampling Requirements

Reducing the sampling intensity—and thus reducing the costs needed to procure imagery and the manpower required to process and review it—also could expand applications for satellite imagery on larger geographic scales. We returned to the Rowley Island data set and overlaid a series of square grids on the island, with cell sizes ranging from 2×2 km to 6×6 km (Fig. 2). Given the high detection rate of bears on the island (Stapleton et al. 2014*b*), we assumed that the observed distribution of bears on the landscape was a reasonable approximation of their true distribution. We extracted counts of independent bears per cell for each grid. These data were counts; therefore, we examined spatial distribution by testing whether they followed a Poisson distribution (evaluated by variance-to-mean ratios, where a ratio roughly equal to 1 suggests that data follow a Poisson distribution; Horne and Schneider 1995). Because Rowley Island comprised a finite population and we were primarily interested in understanding how the methods (i.e., variable grid-cell sizes and sampling intensities) would perform in a real world scenario, we then resampled our data without replacement, sampling from 20% to 90% of the total grid cells per iteration in 10% increments (1,000 iterations/incremental increase). For each iteration, we summed the count data and geographic area from selected grid cells, calculated density from these metrics, and extrapolated by multiplying this density by the island's total geographic area to estimate abundance. We calculated coefficients of variation from simulation results to quantify variability in abundance estimates by percentage of the island sampled and by grid cell size. We hypothesized that because polar bear distribution on Rowley Island appeared nonrandom upon visual inspection, smaller grid-cell sizes would facilitate obtaining reliable estimates of density and abundance when less of the island was sampled than would be facilitated by larger grid-cell sizes. For brevity and to illustrate the spectrum of resampling scenarios that we evaluated, we focus the presentation of resampling results on the 2×2-km, 4×4-km, and 6×6-km grid-cell sizes.

RESULTS

Automating Detection

Percent reflectance.—Reflectance values of polar bears overlapped with nontarget objects: we estimated mean reflectance of presumed polar bears as 0.33 (SD = 0.07) and mean reflectance of nontarget objects as 0.46 (SD = 0.10; Fig. 3). Approximately 98% of polar bear pixels had reflectance values from 0.20 to 0.50; 40% of nontarget samples were 0.50 to 0.60, although reflectance values of nontargets were more variable than values of polar bears. This method correctly identified all known polar bear locations, but it also identified thousands of false-positive "polar bear" polygons (i.e., polygons that represented pixels with reflectance between 0.20 and 0.50 and total areas from $2\,m^2$ to $4\,m^2$). Reflectance, in this case, will not expedite the process of reviewing imagery to identify polar bears.

Image differencing.—Automated image differencing correctly indicated that the vast majority of Rowley Island did not change between target and reference images (e.g., rocks that could be mistaken for polar bears were rarely identified

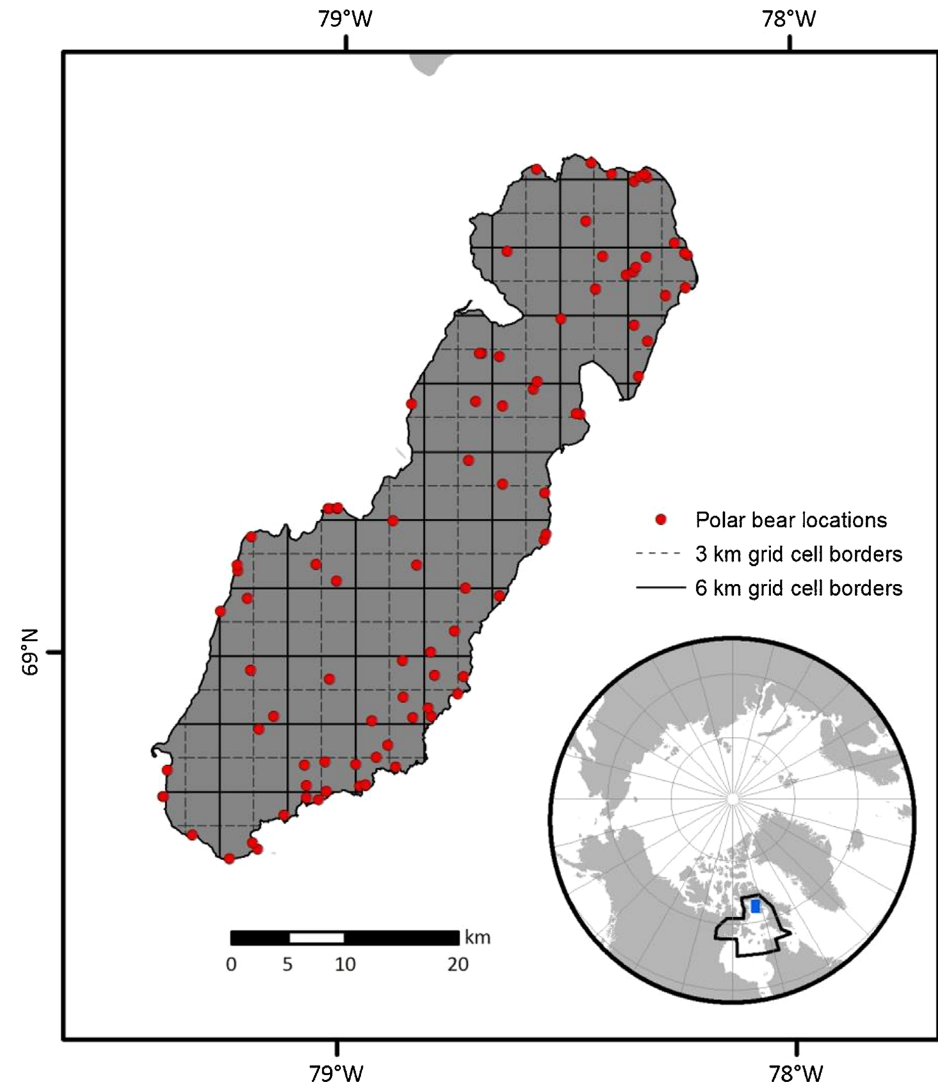

Figure 2. Grids (3 × 3 km and 6 × 6 km) overlaid on Rowley Island in northern Foxe Basin, Nunavut, Canada. Polar bear locations were identified with satellite imagery, which was collected during September, 2012 (Stapleton et al. 2014*b*). The Foxe Basin polar bear population is outlined in black in the inset, with the Rowley Island region shaded blue.

as different by the calculated raster). This finding was expected because the 2 images were taken during the same time of year and, across most of Rowley Island, during the same year (approx. 5-day to 3-week intervals between collections). About 87% of presumed polar bears were easily identifiable with automated image differencing, meaning they were displayed as red pixels (indicating a difference between images) among a landscape of yellow (indicating no difference between images). However, overall reflectance values of the reference imagery from northeastern Rowley Island were high because of different collection parameters from the satellite platform (e.g., off-nadir angle, cloud cover, etc.). Thus, the difference calculation between 2 particular image mosaics resulted in much of the area being incorrectly classified as different because of the fact that the images were taken on different dates such that the satellite parameters were different as well. In other words, the known polar bears in that area were not readily identifiably different from the surrounding landscape. However, this method did expedite the process of reviewing imagery in general because the observer could focus on areas identified as being different rather than manually toggling between the target image and the reference image across the entire site.

Evaluating Sampling Requirements

Count data from grid cells varied by size (Fig. 4) and approximated a Poisson distribution (variance-to-mean ratios: 2 × 2 km: 1.21; 3 × 3 km: 1.35; 2 × 4 km: 1.27; 4 × 4 km: 1.32; 5 × 5 km: 1.74; 6 × 6 km: 1.70). However, there was modest overdispersion across all cell sizes (i.e., variance-to-mean ratios >1), suggesting some clumping in spatial distribution (see also Fig. 2). Estimates of abundance from resampling simulations were highly variable when small percentages of the site were sampled, but greater sampling intensities yielded results that more consistently reflected true abundance (e.g., sampling >50% of study site yielded CVs <15%; Fig. 5; Table 1). Overall, we documented reductions in coefficients of variation of only 18–27% with

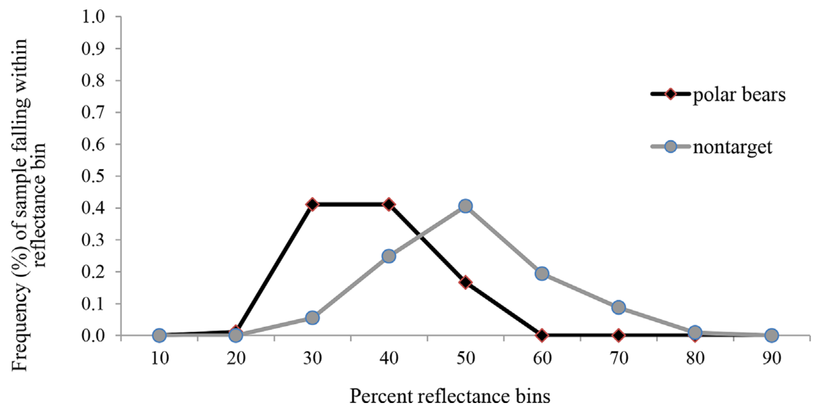

Figure 3. Frequency of samples from WV-02 image acquired in August, 2012 of polar bear pixels and nontarget object pixels on *y*-axis versus the percent reflectance of those samples on the *x*-axis. Most samples of polar bear pixels ranged between 30% and 50%, whereas most non-target pixel ranged between 40% and 70%.

the smallest grid-cell sizes (Table 1), suggesting that cell size may be a relatively unimportant consideration for larger sampling schemes.

DISCUSSION

Automating Detection

Proof-of-concept papers assessing high-resolution satellite imagery as a resource to detect and monitor wildlife are accumulating (LaRue et al. 2011, Fretwell et al. 2012, Lynch and LaRue 2014; McMahon et al. 2014, Yang et al. 2015), yet automatic detection is still at its infancy. For polar bears, automated detection is necessary to expedite image review and facilitate large-scale applications. Here, we present an original design of a semiautomated system for detecting and estimating abundance of large-bodied polar species.

We anticipated that conducting such supervised classification using percent reflectances would be the most effective means to automate detection of polar bears, but this was not feasible for several reasons. Primarily, the mean reflectance values of polar bear pixels were not different enough from other objects on the landscape to allow our computer algorithm (within ArcGIS) to isolate only pixels of polar bears. As such, many of the resulting "polar bear polygons" encompassed random areas on the landscape. Although known polar bear locations were included in polygons, this process also generated thousands of false positives and did not expedite the search process. This finding suggests that there is too broad a continuum of reflectance values for both polar bears and their surrounding landscape to definitively distinguish them with reflectance values derived from panchromatic imagery alone.

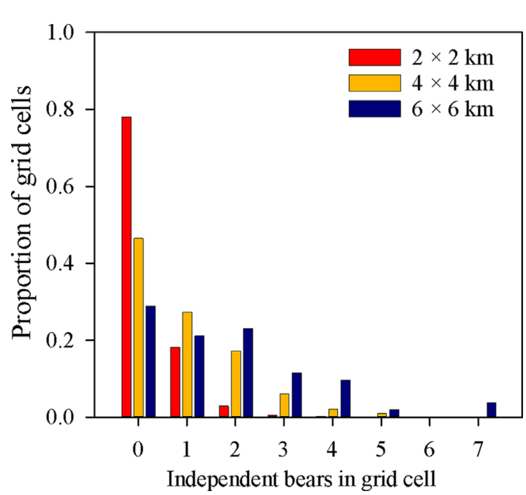

Figure 4. Number of independent bears per grid cell (2 × 2 km, 4 × 4 km, and 6 × 6 km) on Rowley Island, Nunavut, Canada. Polar bears were detected with very high resolution satellite imagery collected during September, 2012 (Stapleton et al. 2014*b*).

We did not attempt to use pansharpened (i.e., higher resolution image created by merging the high-resolution panchromatic image with the lower resolution multispectral image), multispectral imagery to address the reflectance problem because the resolution of our multispectral images was approximately 2 m; pansharpening would introduce the very spectral mixing we would have needed to avoid in order to reliably identify only polar bears with their spectral information. With the advent of the WV-03 and WV-04 satellite platforms (the former was launched by DigitalGlobe, Inc., Longmount, CO in Aug 2014), increased resolution (approx. 0.30 cm pixel size for panchromatic imagery) will be publicly available and may allow for such pansharpening and analyses. However, the current status of image spatial and spectral resolutions (approx. 0.5–0.6-m panchromatic; approx. 2-m multispectral, up to 8 bands) does not permit identification of polar bears via reflectance values or spectral signature.

We found that the most feasible method for automating detection of polar bears on Rowley Island (and presumably for other areas and other large animals) was image differencing, in which the values of the reference image are subtracted from values of the target image to determine differences between the two. Image differencing has been used to identify and estimate populations of horses (*Equus caballus*) in the American West via use of aerial photographs (Terletzky and Ramsey 2014), although historically, this process has been used for detecting broader environmental changes (e.g., phenologies: Rignot and Way [1994], Verbesselt et al. [2010], wetlands: Munyati [2000], Dronova

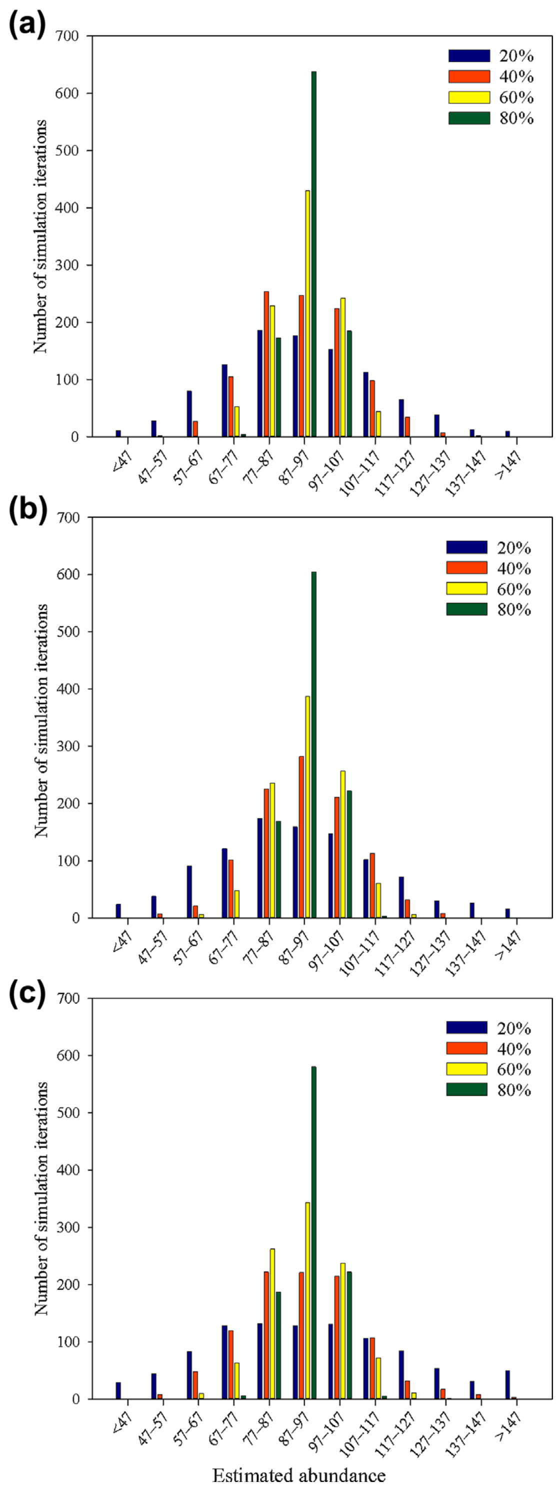

Figure 5. Distribution of abundances of polar bears estimated by resampling grid-cell count data and extrapolating densities. Colors indicate percentage of cells that were sampled per iteration. (a) 2 × 2-km grid cells; (b) 4 × 4-km grid cells; (c) 6 × 6-km grid cells.

et al. [2011], forests: Remmel and Perera [2001], Desclée et al. [2006], Panigrahy et al. [2010], and the Arctic tundra: Jano et al. [1998], Stow et al. [2004]). Here, on relatively flat terrain, the differencing of 2 images shot during the same time of year correctly flagged very little change across much of the landscape (with the exception of the northeastern

Table 1. Coefficients of variation (%) estimated from resampling simulations of polar bear distributional data. $N = 1{,}000$ iterations/plot size and site percentage combination.

	Percentage of site sampled per iteration							
Plot size (km)	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
2 × 2	23.5	18.2	15.2	11.6	9.5	7.3	5.9	3.8
2 × 4	23.9	18.8	14.7	11.9	9.3	8.2	6.1	3.9
3 × 3	25.4	19.7	15.0	12.6	10.4	8.4	6.3	4.2
4 × 4	26.0	18.8	15.0	12.4	10.7	8.0	6.2	4.2
5 × 5	28.8	22.0	17.4	14.8	12.0	9.7	7.2	4.8
6 × 6	31.8	22.4	17.9	14.0	11.7	10.0	6.8	4.7

portion, where differences in collection parameters resulted in substantial differences).

The technique proved effective in capturing most known polar bear locations while reducing the total search area by highlighting pixel clusters for subsequent review. Using VHR satellite imagery to monitor polar bears, therefore, necessitates 2 overlapping images shot during the same time of year; images taken at intervals close together in time are better (Terletzky and Ramsey 2014). Although ice and snow patches were insignificant issues with previous work on Rowley Island, they may pose significant challenges elsewhere and could preclude reliable detection. Differences in snow patches between images collected just a few days to a week apart are likely minimal, however. Using imagery collected in close temporal proximity might improve the capacity of the difference raster to select only polar bears (i.e., fewer nontargets), thereby extending potential applications to regions or time periods with patchy snow cover and onshore ice floes. Depending on the frequency of image acquisition by satellite vendors, overlapping imagery may be missing for many locations. However, as high-resolution satellite imagery becomes more readily used for ecological and conservation research purposes, the availability of overlapping images will likely increase.

Because the ArcGIS satellite-image differencing process only moderately expedites detection and enumeration of polar bears, we recognize that future improvements may be made with more powerful remote-sensing programs. For example, ENVI, ERDAS, and Definiens (Carlsbad, CA; i.e., eCognition platform) are commonly used in remote sensing (Liu et al. 2002, Dronova et al. 2011) and have more capacity to intricately analyze and parse images via object-based image analysis. Though we had originally intended to find a method that could be easily replicated by wildlife biologists, it is possible that solutions could be found using these tools. Indeed, such methods were recently used to automatically detect large animals (e.g., wildebeest [*Connochaetes* sp.]) in the savannahs of Kenya (Yang et al. 2015). There is a trade-off between time consumed conducting research via ArcGIS and the steep learning curve necessary to use complex remote-sensing programs, the latter of which wildlife biologists and managers likely do not have time to learn. Thus, for the purposes of expediting detection and abundance estimation of polar bears across large expanses, we advocate using image differencing in the more readily available ArcGIS. As spatial and spectral resolution advances within VHR satellite platforms, we suspect that methods outlined here may become more desirable.

Evaluating Sampling Requirements

Resampling spatial data from Rowley Island provides some guidance about the sampling intensity necessary to achieve a result that reflects true density and abundance. For a one-time survey, our results suggest that reduced spatial coverage (approx. 20–40%) is likely to yield an inaccurate result, regardless of the size of the sampling plots. We suggest that sampling 50% of the site may represent a reasonable compromise between costs associated with imagery (i.e., procurement and processing) and reliability of results (e.g., CV <15%), but such judgments are at the discretion of individual managers and jurisdictions.

In our study, although different sizes of sampling plots (i.e., grid cells) yielded significant differences in count data, plot size did not impact the reliability of abundance estimation. This finding is important for future applications of satellite imagery. The use of imagery requires direct purchase of the images as well as investing in the manpower to review them, either manually or via a semiautomated process. The time required for image processing and review depends on the total sampling area, but not actual plot sizes. However, plot size is an important consideration for procurement of imagery: larger individual cells more closely approach the minimum size (and thus cost) requirements for satellite imagery, potentially reducing costs of a prospective monitoring program.

We used data from Rowley Island as a proxy for polar bear distributions that may be encountered elsewhere in order to extend our inference, but we are uncertain whether these data effectively approximate distributions at larger spatial scales. We are unlikely to observe such high densities of bears in most locations, and significantly different patterns of distribution may impact our findings. However, we hypothesize that using larger plot sizes in lower density regions may yield results similar to our Rowley Island count data (i.e., approx. Poisson distribution), and we note the similarity of resampling results here regardless of plot sizes. Stratification of sampling by known or presumed density gradients (e.g., proximity to the coastline; Stapleton et al. 2014*b*) is also an important consideration for applications at larger spatial scales.

Very high resolution satellite imagery is among the new tools available to estimate the abundance of large mammals, but more research is needed to understand how this tool can best be applied for studying and managing wildlife. As technologies improve, VHR satellite imagery likely will become more widely integrated in programs for monitoring megafauna, given the safe and cost-effective access to remote sites that it affords researchers.

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