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ORIGINAL ARTICLE

Community-based observing networks and systems in the Arctic: Human perceptions of environmental change and instrument-derived data

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Abstract Many papers have addressed the differing approaches to observation by scientists collecting instrumented data and by community or local knowledge-based observations. Integrating these ways of knowing is difficult because they operate at different scales and have different goals. It would benefit both scientists and communities to integrate community-based observations and instrumented data, despite obstacles, because it would expand scales of observation and because gauged data in the Arctic are sparse. This requires development of a protocol to integrate these knowledge systems to maximize reliability and validity. We used survey data from a community-based observing network in the Bering Sea and examined the correspondence of community-based observations with instrument-derived data for air temperature, sea ice break-up and freeze-up, and vegetation changes. Results highlight that there is a high correspondence between community-based observations for sea ice and vegetation change and instrumented data, but there is an inherent conflict in scales of observation for air temperature data. This helps to elucidate the benefits of community-based observing as a process for understanding and responding to change in the Arctic.

Keywords Community-based observing · Community-based observing networks · Local place-based knowledge · Perception · Environmental change · Instrumented data

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Introduction

The Arctic is at the forefront of environmental change. Due to shrinking ice coverage (e.g., Stroeve et al. 2012), the region experienced its first successful cruise ship navigation last year (Zak 2016). Global surface temperature records (measured from 1880) and Arctic sea ice extent both broke records in the first 6 months of 2016 (Lynch 2016). It is unknown whether these conditions represent a new normal, but change is occurring quickly in the Arctic. This highlights the critical need to document and monitor physical and biological indicators at a variety of spatial scales to better contextualize change relative to natural variability.

Instrument-derived data (IDD) covering the Arctic is limited due to the immense geographic area and relative sparseness of long-term IDD networks, which leads to inability to reliably monitor changes at the community scale. Instrument-derived data experience other challenges including that stations are often located for easy access, or to serve dual purposes (e.g., monitoring weather for air traffic), not to maximize spatial representativeness. Gauges can be inaccurate; for example, precipitation measurements can be biased when precipitation falls as snow, resulting in under-estimation of amounts (Kane and Stuefer 2015). Field research is often limited to summer or fall and typically for short time periods (Eicken and Lee 2013). Station-based observations are advantageous as they provide an in situ measure; however, changes in instrumentation, in observing practices, and movement of the station itself can lead to uncertainty in measurement, resulting in potential challenges in quantifying changes through time (e.g., Karl and Williams 1987). Often, records do not extend far back in time (National Research Council 2006).

Satellite data is increasingly utilized to fill gaps, but coverage over the Arctic is less robust than that in other regions (Magnuson 2014) and accuracy of satellite records is also challenged by satellite drift, varying times of orbits, cloud cover, and issues with algorithms used to convert data (Achard et al. 2001; Wentz and Matthias 2000). Thus, there are challenges with using instrument-derived data, especially data at fine scales in high latitudes (Alexander et al. 2011).

One would expect small communities who are highly dependent on resources that they gather locally, to relatively accurately perceive environmental conditions that affect the location, availability, ability to access, and condition of the resources they gather (Klein et al. 2014; Jolly et al. 2002). Perceptions are likely honed over many years of traveling throughout their environment and observing the most productive areas and circumstances for gathering resources (Alessa et al. 2016a; Fernandez-Llamazares et al. 2015). These communities probably exhibit behavior consistent with optimal foraging theory (Raichlan et al. 2014). Alaska and the Arctic are populated with many communities that meet these criteria, including those who collaborated in this study. We refer to observing programs in these communities, which are organized to systematically collect and document observers' recollections of change, as community-based observing networks and systems (CBONS) (Alessa et al. 2016b).

We propose that integrating CBONS into existing observing systems across the Arctic in a human sensor-array, and coupling them with instrumented records, would improve our collective abilities to understand and respond to changes, particularly at local scales (Eicken and Lee 2013). Observing networks are currently used to record Arctic events and changes as part of scientific monitoring efforts (Alessa et al. 2016b). In Alaska, networks include, but are not limited to the Arctic Ocean Observing System, the Global Ocean Observing System, the Arctic Observing Network, and the Sustaining Arctic Observing Network (Alaska Ocean Observing System 2016). Including observations from local communities organized as CBONS can provide data at local scales to complement the relatively sparse IDD and serve some of the needs of scientists and the communities.

Humans as observers

Many scientists exhibit a level of distrust of observational data (Berger et al. 2009; Dickersin and Berlin 1992). Indeed, our perceptions are not an accurate representation of objective reality (Stefanucci and Proffitt 2009; Witt and Dorsch 2009), and perceptions are limited in time and scope (Hoffman et al. 2015). Studies suggest that our perceptions are biased by attending to information that supports our worldview and discounting information that contradicts it (Lavie et al. 2004). We assess options based on prior experience (Pachur et al. 2012). There is significant feedback between our expectations and our perceptions (Clark 2013). Perceptions are a complex interaction among the observer, the environment, and the social context in which an observer is found (Stefanucci and Proffitt 2009; Witt and Dorsch 2009; Hoffman and Prakash 2014). Finally, perceptions are stored as memories and memories are modified each time we retrieve them. These modified memories are used to categorize and respond to current perceptions (Marsh 2007).

It is important to acknowledge the limitations and benefits of both instrumented data and CBON observations. Ideally, all data collection should be assessed to increase the reliability and validity of the data. There is a long tradition in the scientific community of calibrating instruments to increase their accuracy (Csavina et al. 2017; Gupta 2012). If we can understand how best to calibrate human observations, it could be possible to combine observations to provide the most complete and accurate representation of change.

The communities who collaborated in our study and local place-based knowledge (Indigenous knowledge and traditional ecological knowledge)

The Bering Sea Sub-Network (BSSN) and its successor, Community Observing Network for Adaptation and Security (CONAS), is composed of eight communities bordering the Bering Sea in the Russian Federation and Alaska, USA. The Russian CONAS communities who collaborated in this study are Nikolskoye (Western Aleut/Unangas), Tymlat (Koryak), and Kanchalan (Chukchi); in Alaska, participating communities included Gambell (Siberian Yupik), Savoonga (Siberian Yupik), Togiak (Central Yup'ik), and Sand Point (Eastern Aleut/Unangan). CONAS is a partnership of communities across the Bering Sea to collect information for the purposes of adaptation, decision-making, and development of a community-based early warning system (CONAS n.d.). The location of these communities is depicted in Fig. 1 below.

These communities are predominantly Indigenous and have long traditions of gathering food from their environment primarily because of the cultural importance of subsistence, but also because of the prohibitive cost of transporting food (Brewster 2004). Populations of the Russian communities range from 500 to 800 people (Russian Census 2010). Economies are dependent on fishing; hunting seals, walrus, and whales; gathering plants for food; and making and selling small handicrafts (Yamin-Pasternak personal communication).

In Alaska, community populations range from 700 to almost 1000 at Sand Point (U.S. Census 2010). All communities are primarily Alaska Native except Sand Point, whose population is about half Alaska Native (U.S. Census 2010). The more northerly communities rely on whales, all communities rely on walrus and seals, and the more southerly communities also rely on fish. All communities fish and gather berries and plants for food (Alaska Department of Fish and Game 2016). Use of subsistence foods is estimated to range from 80 to 500 lb per capita per year (Alaska Department of Fish and Game 2016). Subsistence underpins the economies of all of these communities except Sand Point (Alaska Department of Fish and Game 2012). Sand Point's economy relies equally on subsistence and commercial fishing (Sand Point 2014).

The knowledge contributed by these communities is local place-based knowledge (LPBK) that also incorporates

Fig. 1 Map of members of the Bering Sea Sub-Network (now CONAS) who collaborated in this study and location of two communities in which air temperature stations are located

Indigenous knowledge. In this paper, because of the demographics of the communities included in the study, we use the terms community-based knowledge and local place-based knowledge synonymously, and we refer to this knowledge as community-based observing (CBO). Community-based observing and Western science are similar because both are based on an accumulation of observations. Descriptions of CBO vary, but most include (1) detailed systematic observations of the environment of a specific place through direct interaction, (2) an active process that includes new information and knowledge handed down through generations by oral transmission (i.e., narrative teaching) (United Nations 2008; Ramnath 2014; Smith et al. 2014), and (3) a holistic understanding of ecosystems and interactions with human socioeconomic systems (Berkes et al. 2000). Unlike instrumented data, CBO is not often committed to writing and time scales span human generations.

Fienup-Riordan and Carmack (2011) define Western science as (1) investigations based on the scientific method, (2) a body of techniques for formulating and testing hypotheses, and (3) based on systematic observation, measurement, and experiment. Scientists typically view Western science as analytical, reductionist, positivist, objective, and quantitative (Fienup-Riordan and Carmack 2011; Ramnath 2014). In this paper, following Alexander et al. (2011), we define Western science as "a set of statistically analyzed data or instrumental records . . . that can be empirically measured and that demonstrate acceptable levels of reliability and validity" (p. 477). The data are sometimes available on websites and often in scientific journals.

In a changing Arctic, CBO has much to offer, although integration with Western scientific approaches can be difficult because of issues associated with data types and interoperability as discussed below. The challenge of integrating these two ways of knowing has led to the underutilization of CBO (Huntington et al. 2004). Nonetheless, CBO has made contributions to place-based adaptation research by elucidating vulnerability to environmental change and exploring appropriate adaptive actions and interventions (Pearce et al. 2009; Brubaker et al. 2011; Collings 2011; Ford and Pearce 2012), among other uses and goals.

Community-based observations of change in the Arctic

In this study, we assumed that observers who rely on the land and sea for their food may be particularly adept at observing and reporting complex ecological systems (Smith et al. 2014). Only a few studies have compared community-based observations to IDD. An understanding of the circumstances under which community-based observations are better measures of change would be beneficial in the continued use and evolution of CBONS as well as in understanding what role CBONS can play in documenting change in the vast geographic area of the Arctic.

Studies that have compared IDD and CBO include that of Prno et al. (2011) who found agreement between scientific literature related to trends in temperature and precipitation and observations of changes to sea ice by residents of Kugluktuk, Canada. Fienup-Riordan and Carmack (2011) documented a correspondence between Western studies and traditional ecological knowledge understanding of the response of sea ice to ocean waves, swells and tides, the formation of shore ice and ice piles, and changes in timing of breakup and freeze-up in villages along the west coast of Alaska. Inuit elders in the Foxe Basin, Canada, characterized the summer ice conditions and late freeze-up of 2006 as being "unprecedented in living memory" and instrumented records supported both observations (Ford et al. 2008). Weatherhead et al. (2010) examined a 50-year record of temperature data in the Clyde River/Baker Lake region of Nunavat, Canada, confirming local residents' observations that weather was less predictable due to a significant increase in its variability.

Herman-Mercer et al. (2011) compared local observations of weather, river conditions, flora, and fauna in two small villages on the lower Yukon River, Alaska, and Huntington et al. (2004) compared local observations of plants, lichens, and insects across northern Canada and northwest Alaska to scientific observations at regional scales. Both studies found correspondence in most observations. We argue that these studies are not unique to Indigenous populations but apply more broadly to place-based local knowledge or community-based observations generically.

Other research has found a lack of correspondence between CBO and IDD. Gearheard et al. (2010) compared wind data with observations at Clyde River, Nunavut, Canada, and found little correspondence between observations and instrumented data. Alessa et al. (2010) found less accurate perceptions of change in water quality and quantity from younger observers compared to middle-aged and older observers in western Alaska. Ambrose et al. (2014) found expert fishers in Kotzebue Alaska to be more sensitive to environmental change in marine species compared to elders and expert hunters. These studies suggest that CBO may be more accurate for those who have the most experience with the specific environmental condition. In this paper, we explore whether observations of community members who had extensive experience in their environment corresponds with IDD.

Methods

Comparing data collected from different sources using different methods is a challenging endeavor. For this work, we rely on social data collected through extensive interviews conducted from 2010 to 2012 and compare them to biophysical data collected from ground station and satellite measurements. For each dataset, we discuss measurement uncertainty and possible sources of error, since understanding the quality of the measurements is necessary to provide us with confidence in the data and subsequent analysis (for a more complete discussion of uncertainty analysis, see Csavina et al. 2017). We also capture uncertainty in the analysis by reporting *p*-values, using a 95% confidence interval to denote statistically significant findings.

Social data

Interviews and questions were developed in participation with, and pilot tested by, members of the communities. Community research assistants (CRA) were hired in each community and trained to conduct interviews. Community experts and CRAs identified elders and community members with at least 15 years of fishing and hunting experience, who were invited to participate in face-to-face interviews. Consent was obtained from all participants. Questions were asked at all locales in languages appropriate to the survey respondents: English, Russian, Yup'ik, or Siberian Yupik. Data protections were dictated by the communities.

Respondents were first asked whether he or she had observed change in an environmental condition. Those respondents who had observed change were asked what changes they had observed, direction of change, season of change (for air temperature), and when they had first noticed the change (see Online Resource 1). For example, with respect to air temperature, survey participants were asked: "Have you observed any changes in air temperature in the past 15 years or longer? a. Yes, b. No, or c. Don't know." If participants responded yes, they were asked: "What changes did you observe in air temperatures in the past 15 years or longer in these specific time periods? In summer, in fall, in spring and in winter?" The response options for direction of change in the survey were "a. increase" and "b. decrease," or "a. earlier" and "b. later." With respect to vegetation changes, respondents were asked two questions: "Have you observed changes in timing of first green grass in spring in the past 15 years or longer?" And "Have you observed changes in vegetation other than grass in the past 15 years or longer?"

Chi square goodness of fit was used to analyze the question of whether change had occurred. If there were significant numbers who perceived change, chi square goodness of fit analysis was also run on the direction of change. When we analyzed direction of change, we included the number of respondents who said that change had not occurred, so that we were comparing all responses (e.g., increase, decrease, and no change) and not just those who had perceived change. We assumed equal distribution of answers to investigate statistical significance, which was set at 0.05. Chi square analysis indicates significance when a response category is significantly larger or smaller than expected. It is important to eliminate don't know/no answer (DK/NA) responses in analysis to assure that significance is not achieved solely because a small percentage of respondents selected this response. To avoid confusion, tables include chi square results excluding DK/NA responses only when significance was affected.

To determine the decade during which we compared perceptions to instrumented data, we calculated the mean years of residence and mean years of hunting and fishing for each community (Table 1). We subtracted the mean years of residence and the mean years of hunting and fishing from the year in which the survey was administered to determine the approximate year that observations began in order to determine the decade to which to compare observations. (The range of years of residence is also included in Table 1.) We used mean years of hunting and fishing for comparison because it is unlikely that residents began observations of environmental conditions at birth, and more likely that gathering resources (hunting and fishing) sharpened respondents' observations.

Biophysical data

We surveyed the availability and quality of biophysical IDD across the study area. The biophysical data we used included air temperature, studies and satellite imagery that assessed freeze-up and break-up of ice for Savoonga and Gambell, and satellite imagery to assess changes in vegetation phenology for villages.

Air temperature

We used two sources of temperature data to track changes near individual communities: (i) station data from the Global Historical Climatology Network (GHCN) and (ii) gridded data from Climatic Research Unit (CRU) dataset CRU TS3.4 (Harris et al. 2014). Using two different sources of data also allowed us to account for structural and observational uncertainty inherent with climate datasets. While station-based observations may be considered to be more representative, they are subject to microclimate influences, to changes in instrumentation practices, and they may contain gaps in observations. By contrast, gridded climate data are temporally and spatially complete and often incorporate station-based observations that have been adjusted for changes in observational practice. However, spatial interpolation of data in data-sparse regions may overlook spatial features (e.g., differential rates of warming for coastal versus more inland locations). The two datasets used here should not explicitly be considered independent of one another as some of the station data was likely incorporated in the gridded estimates.

Monthly mean temperature in both datasets was defined as average of daily maximum and minimum temperature within each month. We required stations to have at least 90%

Table 1 Mean years of residence, mean years hunting and fishing, mean year observations began, and range of years of observation of air temperature

Community	Mean years of residence	Mean first year of observation (residence)	Mean years of hunting or fishing	Mean first year of observation (hunting and fishing)	Years observations began (range)
Gambell	48	1965	38	1975	1925–2006
Kanchalan	42	1968	27	1983	1949–1992
Sand Point	41	1972	29	1984	1935–2003
Savoonga	54	1959	40	1973	1927–1995
Togiak	42	1971	30	1983	1937–2003
Tymlat	33	1978	30	1981	1956–2000
Nikolskoye	37	1977	31	1983	1955–1999

complete data from 1950 to 2011. Station data from GHCN (version 3, adjusted data to correct for station changes) were available within 10 km of several Russian villages. The closest long-term GHCN station data for all Alaskan villages was more than 100 km away (Fig. 1). The climate station at Nome was used to estimate air temperature at Savoonga (262 km to the east) and Gambell (317 km to the east). The King Salmon station was used for Togiak (220 km west) and Sand Point (438 km south). While less than ideal, the spatial autocorrelation of temperature is typically quite large (correlation decay distance of 500 km is typical for high-latitude landmasses (New et al. 2000)) allowing remote observations to be acceptable proxies of change. As an alternative, the CRU TS3.4 dataset spatially interpolates anomalies in monthly station data to develop a temporally complete grid of land surface temperature at a 0.5° spatial resolution. We used collocated grid cells for each village. For cases where there was no grid cell with temperature collocated with the village (e.g., some islands), we chose the closest grid cell (based on minimum distance) with temperature data.

A simple linear least squares trend test was performed separately for each station on both the station-based and gridded datasets. Trends were calculated for the climatological seasons of winter (December–February (DJF)), spring (March–May (MAM)), summer (June–August (JJA)), and fall (September–November (SON)) as well as for the calendar year. Linear trends were computed for six different temporal windows to account for varying magnitude and direction of trends based on the length of the record, all ending in 2011. We chose 2011 for the end year because it was the nearest year during which the survey was administered. Trends were calculated starting the years of 1950–2011 and staggered every 10 years through 2000–2011. Trends were considered to be statistically significant using the Mann-Kendall test where $p < 0.05$.

Timing of ice break-up and freeze-up

We assessed ice cover using passive microwave data at 25-km spatial resolution from SMMR and SSM/I instruments for the years 1979–2012. A threshold value of 15% sea ice concentration for at least 2 consecutive days was set to detect the freeze-up and break-up period for each pixel, and to remove spurious occurrences of low-sea ice conditions. Significant trends in ice persistence were investigated using least squares regressions. An additional comparison of ice persistence for the years 2003–2010 was conducted using ice concentrations from the AMSR-E sensor which has a spatial resolution of 6.25 km. A Theil-Sen median slope estimator was used to assess the rate of change in ice persistence because it is well suited for time series data that are short and/or noisy. Significance of the Theil-Sen trends ($p < 0.1$) were identified using a Mann-Kendall test for monotonic trends (Frey et al. 2015).

A number of scientists have studied ice break-up and freeze-up in the Bering Sea. Studies by Grebmeier (2012) and Frey et al. (2015) suggest that the ice in the Bering Sea has been more persistent, at least since about 2003, based on analysis of satellite records. Stroeve et al. (2014) used an algorithm to detect changes in emissivity of passive microwave data to detect the amount of water and snow on ice that would signify melt or freeze conditions. Stroeve et al. (2014) did not find earlier melt onset in the Bering Sea. However, increasing sea surface temperature around St. Lawrence Island (Shimada et al. 2006) and increasing heat flux through the Bering Strait (Woodgate et al. 2010) could affect ice formation and break-up times at local scales.

Vegetation change

We measured regional vegetation change using a moderate-resolution imaging spectroradiometer (MODIS) satellite imagery for each of the communities. Specifically, we used the MODIS 16-day Normalized Difference Vegetation Index (NDVI), MOD13Q1 composite available through Google Earth Engine (https://earthengine.google.com/). NDVI is regularly used to measure vegetation change and has proven particularly effective in the Arctic and subarctic (Jia et al. 2003; Stow et al. 2003; Verbyla 2008; Pattison et al. 2015). The 16-day composite is especially useful in northern coastal communities where cloud cover often reduces the utility of individual images. As with all measurements, there are uncertainties associated with pixel values recorded by the MODIS sensor. The sensor is designed and calibrated to measure surface reflectance to within ± 2% of actual reflectance, and it has consistently met or exceeded this requirement (Xiong et al. 2007).

We calculated the mean NDVI for a 50-km buffer around each village location (with ocean areas removed) to represent the general community area of use, i.e., the area identified by respondents as where they hunt and gather food. Our analysis begins in 2000 (the first year of MODIS) and runs through the survey period for each village. On average, there were 278 composites available for each village, with a month of missing data each winter due to darkness in the highest-latitude villages of Kanchalan, Gambell, and Savoonga.

Long-term NDVI trends were analyzed using seasonal decomposition of time series by Loess (STL) (Cleveland et al. 1990). STL works by removing seasonality to assess long-term trends in NDVI (see Online Resources 2a and 2b for examples of the decomposition of the Sand Point NDVI data). We also extended the STL analysis by extracting the growing season start day (green-up) and growing season length by using the TIMESAT (Eklundh and Jönsson 2015) extension for Matlab. This method fits an asymmetric Gaussian model suitable for capturing inter-annual changes in vegetation seasonality (Jönsson and Eklundh 2002). Growing season start day and length were calculated from this fitted curve by extracting the midpoint of the seasonal amplitude. Since some of the MODIS imagery is affected by cloud cover, we assigned poor-quality observations (> 30% cloudy), a weight of 0.1; moderate-quality observations (10–30% cloudy), a weight of 0.5; and good-quality observations (< 10% cloudy), a weight of 1.0. We then look for trends in the growing season metrics by fitting a linear model and also evaluating the non-parametric Mann-Kendall test. To clearly show the uncertainty associated with this trend analysis, we report p values for each village.

Results and discussion

Air temperature

Alaskan communities

A statistically significant number of Gambell, Savoonga, and Sand Point respondents observed that there had been no change in air temperature. However, a statistically significant number of Togiak respondents agreed that change had occurred, both when including and excluding DK/NA responses. Togiak respondents perceived no change in spring, summer, and fall temperatures, but a significant number observed that winter was warmer (Online Resource 3).

Russian communities

Statistically significant numbers of respondents in all Russian communities observed that air temperature had changed when DK/NA responses were included. When those responses were excluded, change responses were still significant (although at a lower level in Kanchalan) except in Tymlat where the answer that change had occurred was no longer significant, indicating that Tymlat respondents did not perceive a change in air temperature in significant numbers. In analyzing direction of change (increase, decrease, or no change), the significant response in Kanchalan was that no change had occurred in any season. Nikolskoye respondents agreed that no change had occurred in spring and fall. When DK/NA responses were eliminated for that community, there was no significant response for summer or winter. In summary, a statistically significant number of respondents in all communities perceived that no change had occurred in any season except Nikolskoye whose responses were not significantly different between an increase and a decrease in temperature (Online Resource 4).

Two sources were used for IDD in this study as described above. In Fig. 2 below, the left side represents station data. The right side represents the composite gridded data from the Hadley CRU. As discussed above, station data located within the communities were only available for the Russian communities. Statistically significant long-term warming trends (i.e., 1950–2011, 1960–2011, 1970–2011) were apparent for most communities in both gridded and station-based temperature records for annual mean temperature and summer temperature. Notably, statistically significant cooling was seen in winter and spring temperature trends covering the time periods 1990–2011 and 2000–2011 for Togiak and Sand Point, Alaska. While there were some differences in trends by station and between station observations and gridded estimates, we see broad-scale agreement in temperature trends across the region particularly at longer (> 30 year) time scales.

Ice break-up and freeze-up (Gambell and Savoonga)

A statistically significant number of survey participants in both Gambell and Savoonga agreed that sea ice freeze-up was occurring later and that break-up was occurring earlier. Table 2 below provides the counts and statistics of sea ice perceptions.

General trends in sea ice are well documented (thinning, decrease in extent, change in timing of freeze, and thaw), but changes vary regionally with some areas not experiencing any change (Meier et al. 2011). At regional scales, the Bering Sea did not show decreasing sea ice persistence (Frey et al. 2015) or earlier melt onset (Stroeve et al. 2014). However, there was a statistically significant decline in the number of days of sea ice persistence around Gambell and Savoonga from 1979 to 2012 using SSMR and SSM/I gridded data (Frey et al. 2015),

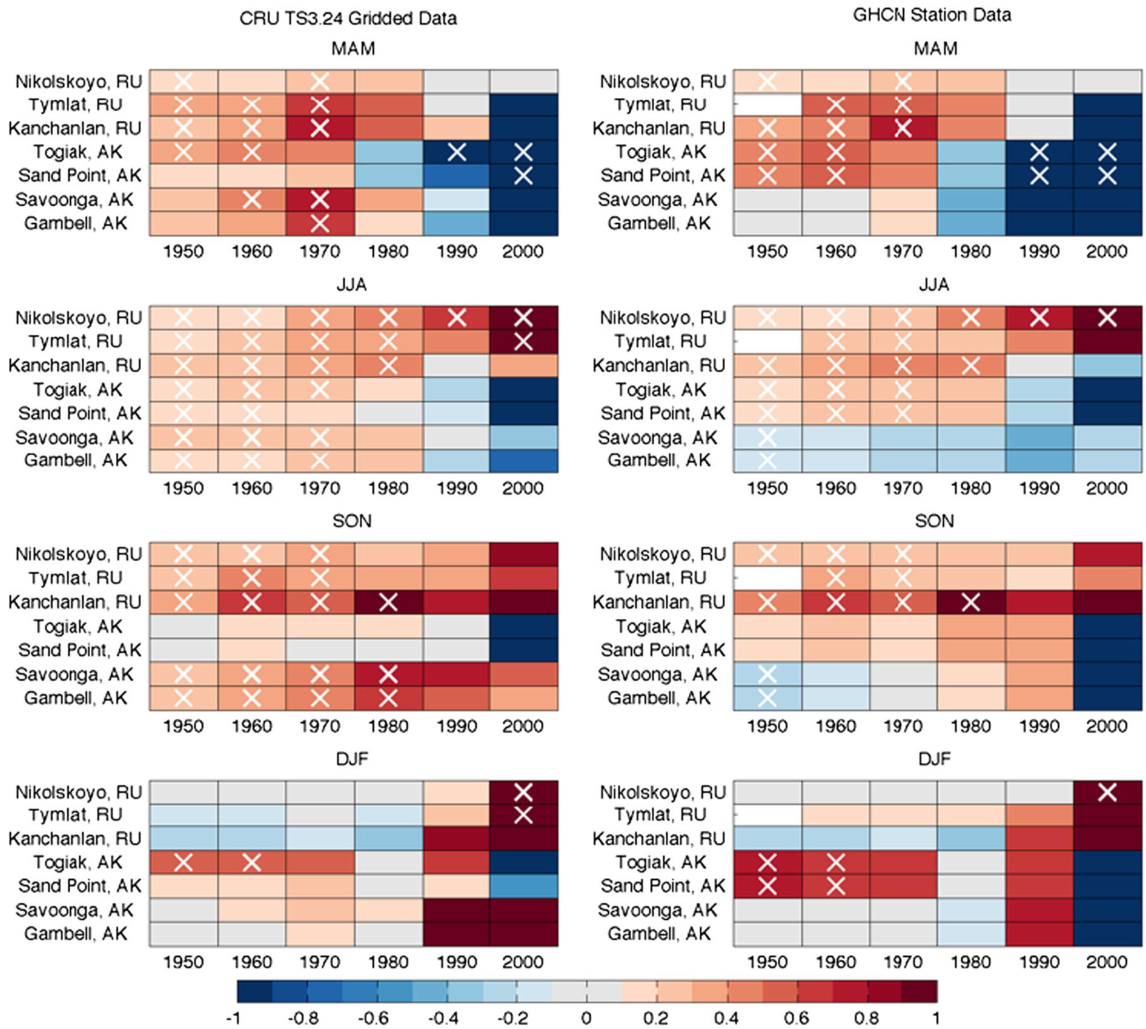

Fig. 2 Linear least squares trends in mean air temperature for each of the seven villages from the (left) CRU TS v3.24 gridded data and (right) from the closest long-term GHCN station to each village. Trends, reported in degree Celsius per decade, are calculated for the (from top to bottom) March–May (MAM, spring), June–August (JJA, summer), September–November (SON, fall), and December–February (DJF, winter). Trends are computed for six different time periods all ending in 2015, with the leftmost column showing trends from 1950 to 2015, the next column showing trends from 1960 to 2015, and so on. Trends that were statistically significant per the Mann-Kendall test at $p < 0.05$ are denoted by a white x

but no significant decreasing trend in sea ice persistence from 2000 to 2012. There was also no significant decreasing trend in ice persistence from 2003 to 2010 around Gambell or Savoonga using the AMSR-E data at 6.25-km spatial scales.

Table 2 Counts and chi square analysis results of Savoonga and Gambell Alaska observations of break-up and freeze-up of sea ice. Analysis excluding don't know and no answer responses is only included when it changed significance levels. *Significant at 0.05 level. **Significant at 0.01 level

		Gambell	Savoonga
Freeze-up	Earlier	8	8
	No change	26	13
	Later	36	26
	Don't know or no answer	7	5
	Chi square including don't know/no answer	$\chi^2 = 31.312$ df 3 **	$\chi^2 = 19.846$ df 3 **
Break-up	Earlier	43	24
	No change	21	17
	Later	3	3
	Don't know or no answer	10	6
	Chi square including don't know/no answer	$\chi^2 = 47.623$ df 3 **	$\chi^2 = 22.800$ df 3 **

Table 3 Counts and chi square statistics for observation of change to grass. Analysis excluding don't know and no answer responses is only included when it changed significance levels. *Significant at 0.05 level. **Significant at 0.01 level

Village	Grass has changed (earlier/later)	No grass change	Don't know or no answer	Chi square including don't know	Chi square excluding don't know
Alaskan villages					
Gambell	7/5	59	6	$\chi^2 = 65.636$ df 2 **	
Sand Point	7/28	65	4	$\chi^2 = 53.200$ df 2 **	
Savoonga	7/1	37	6	$\chi^2 = 33.731$ df 2 **	
Togiak	28/14	94	14	$\chi^2 = 65.179$ df 2 **	
Russian villages					
Kanchalan	4/2	38	6	$\chi^2 = 40.960$ df 2 **	
Nikolskoye	7/16	44	17	$\chi^2 = 13.859$ df 2 **	$\chi^2 = 5.882$ df 1 *
Tymlat	1/1	46	2	$\chi^2 = 74.235$ df 2 **	

One potential source of error when comparing CBO with IDD comes from the methodology used to detect trends with a regional focus using remote sensing data. Stroeve et al. (2014) considered whether each pixel was within one standard deviation of 5 × 5 spatial neighborhood to be included in the statistical analysis of melt and freeze onset. However, each village may only encompass observing conditions within a single pixel at the 25-km spatial resolution, and it may be less appropriate to assess homogeneity of landfast ice conditions compared to ice cover in open water. Landfast ice, sometimes called shore-fast ice, is young coastal ice that builds seaward from the shore of a landmass. Unlike pack ice in deep waters, landfast ice attaches itself to the coastline and does not drift with currents and wind (Mahoney et al. 2006). Setting a 15% sea ice concentration threshold to detect freeze-up and break-up conditions is also well suited for a regional-scale analysis, but would not distinguish landfast ice that is emphasized in CBO observations of break-up and freeze-up.

Vegetation change

A statistically significant number of respondents in each village perceived no change in grass or vegetation. Since the vegetation question did not specify which changes respondents were observing, we determined that changes to grass would more clearly relate to an analysis using NDVI and we used only that survey question for analysis as shown in Table 3 below. A statistically significant number of participants in each community agreed that the timing of grass green-up had not changed.

Figure 3 shows the growing season start day for each village; this metric matches the grass green-up survey question most closely. The statistical analysis using linear regression models and the Mann-Kendall trend test show no trends in the start of the growing season, except for Nikolskoye whose green-up period appears to have shifted earlier by about 1 day per year on average starting in 2000 (Fig. 3 and Online Resource 5). In addition to season start day, we assessed changes in the length of the growing season (Online Resource 6) and found no statistically significant trends (Online Resource 7). Lastly, we looked for overall trends in vegetation change, independent of seasonality, by evaluating total NDVI over the time period both statistically (Online Resource 8) and graphically after removing the seasonal component (Online Resource 9) and found no trends over time. The majority of community observations and IDD correspond, suggesting that changes in timing of grass green-up are not occurring in this area.

Discussion and conclusion

The year that each survey participant began his or her observations varies, and because environmental conditions (some more than others) vary from year to year, the conditions each survey participant uses to assess whether change is or is not occurring will also vary. Each survey participant is likely to have different environmental conditions in mind when assessing whether change has occurred, that is, they will have different bases of comparison. Survey participants who are closer in age may have similar bases of comparison. Those who are separated by a generation will likely have very different bases for determining what is changing and what is not. Older generations will have experienced a decade or more of conditions that the younger generation has not. The differing bases of comparison of different generations has been documented in other studies by Fernandez-Llamazares et al. (2015) and Alessa et al. (2008). Table 1 illustrates the basic incongruence between the need of climate scientists for long-term records to document trends in data with large variability, such as air temperature, and the shifting base of reference of human perception.

Only a few of the respondents from these communities will have closely observed their environments since 1950 when our air temperature analysis began. Most started hunting and fishing in the 1980s. Significant trends in IDD in Alaska communities

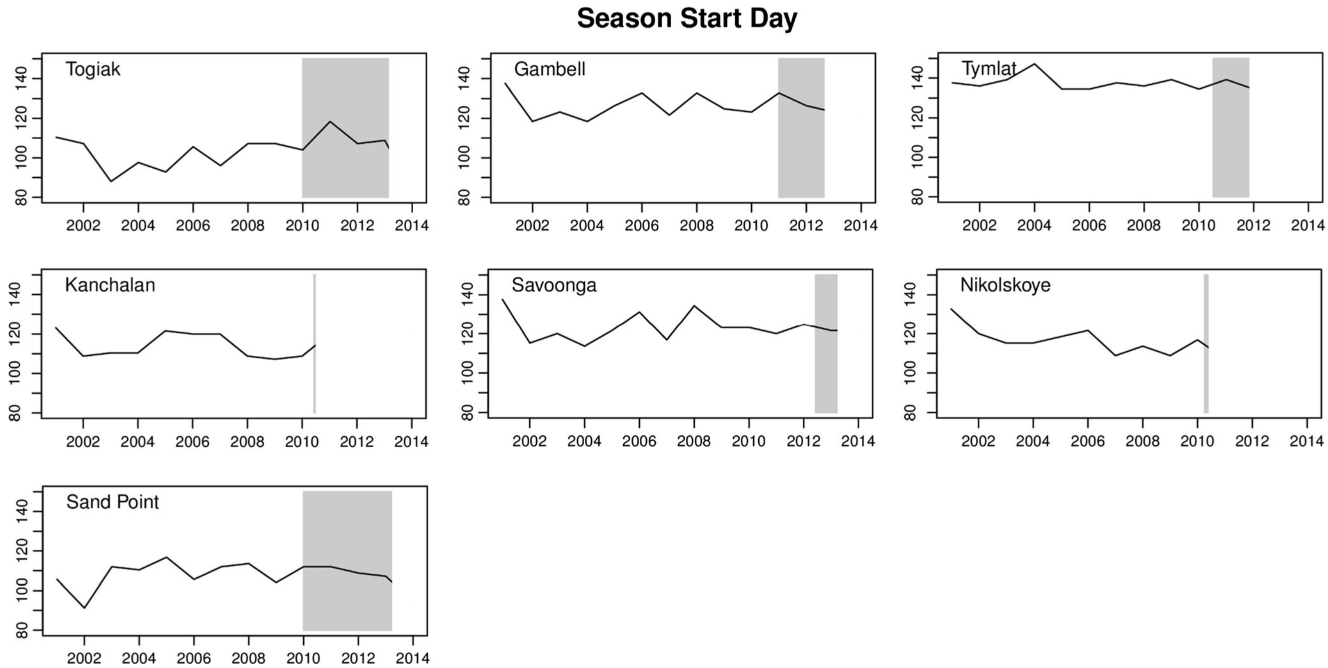

Fig. 3 Season start day for each village. Plots derived from 16-day MODIS NDVI time-series data. The survey period is highlighted in gray

from the 1980s forward include significant cooling in Togiak and Sand Point Alaska during spring, and significant warming during the fall in Savoonga and Gambell (both datasets). However, the fall warming trend is not significant after 1980 when most observations began. In the Russian communities, both datasets show a significant warming trend in summer for Nikolskoye and Kanchalan. The CRU dataset shows a significant warming trend for Tymlat during the summer, but the station dataset does not. The only community for which that trend continues through the ensuing decades is Nikolskoye. Both datasets show a significant increase in fall temperatures in Kanchalan from the 1980s but not in the following decades.

Air temperature observations illustrate an underlying incongruence between the need for long-term observations to detect trends and the shifting basis of reference of human perception. To adequately compare temperature data to IDD trend data (which requires at least 30 years of observations), one must select older survey participants and selectively compare IDD beginning at the same time as their observations. Increased statistical power requires a large sample size of older respondents, which is difficult to realize in these small communities. With a few exceptions, trends in the biophysical data are less clear after the 1980s. This may be reflected in the responses of our survey participants whose DK/NA responses were frequently the significant response, or there was not a significant difference among no change, DK/NA, increase, and decrease responses.

For ice break-up and freeze-up, it is important to be critical of whether IDD definitions of ice conditions are comparable to CBO descriptions of freeze-up and break-up. Community observations of sea ice break-up may not necessarily equate to low concentrations of ice or ice-free conditions, whereas remote sensing analysis focuses on reaching a threshold of 15% sea ice concentration. The relationship between subsistence hunting success and sea ice concentrations is also complex and can vary by scale (Huntington et al. 2013); therefore, all comparisons of community observations with remote sensing data need careful consideration of the limitations in scale or detectability of the ice conditions in question. Notably, despite the high inter-annual variability in the timing of freeze-up and melt onset consistent with the variable ice regime described for the Bering Sea (Robards et al. 2013; Stroeve et al. 2014), community observers in this study detected a significant change in the timing of break-up and freeze-up. When scales of observation are consistent, IDD and perceptions match.

Similar to sea ice observations, remotely sensed definitions of green-up could be different than CBO-based definitions. Satellite observations of vegetation change are challenged by cloud cover and by the pixel values recorded by the MODIS sensors. Pixel values consistently met or exceeded ± 2% of actual reflectance, but are sensitive to the spatial scale of the pixel. Green-up, or defining the growing season, from a CBO perspective could be based on finer-scale observations or very subtle differences in color. MODIS pixels are 250 m by 250 m (over 6 ha) and therefore require a relatively large area to change color to reflect a "green" signal. By averaging the NDVI pixels over the buffered area for each village, we not only capture the vegetation signal in the area identified by the community as its subsistence gathering area, but also minimize sensor errors associated with individual pixels. From a CBO perspective, it could be hard to quantify green-up as there are natural gradients in how and when grass might begin photosynthesis. Density of grasses, microtopographic features, and surrounding vegetation could all influence a respondent's ability to detect a change in grass color, adding potential uncertainty to estimates. Despite these sources of uncertainty, a statistically significant number of respondents correctly perceived that no change had occurred in growing season/first green-up.

Our results suggest that human perception of air temperature may not be a reliable substitute or supplement to IDD. A study by Weatherhead et al. (2010) suggests that increased variability in weather made prediction more difficult for similar respondents. This study suggests that perceptions of ice conditions and of grass green-up are more reliable substitutes or supplements to IDD. There are several other studies that document accurate perceptions of ice conditions including those of Prno et al. (2011), Fienup-Riordan and Carmack (2011), and Ford et al. (2008). At least two other studies conducted by Herman-Mercer et al. (2011) and Huntington et al. (2004) confirmed accurate perception of changes to vegetation. The air temperature records we used started in 1950s whereas the satellite data used for ice and vegetation started much earlier. This suggests that observations over longer periods of time may not match IDD as well as observations over shorter time periods.

As an approach, CBO and CBONS, in particular, are becoming increasingly important in providing context and local-scale measurements to data gathered by instruments in the Arctic and across the world. Community-based observing networks currently provide data on a range of variables such as ice conditions, resource availability and quality, phenology assessments, weather and shore-line processes, identification of whales and other mammals, and oil spill reports. With the help of instrumentation, these communities assess water quality and quantity, measure greenhouse gases, sample phytoplankton and algae, and report outbreaks, among other observations (Alaska Ocean Observing System 2016). In the past, CBOs have informed scientists about orca and humpback whale activity and abundance (Brewster 2004). Alaska populations travel by foot, boat, air, and snow machine to remote areas of the Arctic that may not be continuously observed by satellite and in which surface gauges supporting IDD are not currently located. Nationally, there is increasing interest in the use of citizen observations but a science of CBO is immature (Alessa et al. 2016a). As part of this science, toward producing fair, equitable, reliable, and interoperable data, we need to systematically assess how CBO can be co-developed by communities on the ground and by users including scientists, response agencies, and policy makers.

It is important to understand under what conditions CBONS data correspond to IDD and when more accurate assessment of change incorporates both types of data because of differences in definition of phenomena, scales of observation, or perspective. Such an understanding would help determine how observing systems can be combined in the most effective way. In circumstances where differences cannot be explained, it might indicate that a community has reduced capacity to adapt because it is not perceiving changes, or that it is adapting to changes that are not actually occurring, or that it is adapting to changes that are actually occurring but are not currently detectable by IDD (Alessa et al. 2008, 2010). Mapping and communicating the differences between perceptions and instruments could improve the adaptive capacity of communities, and it could refine the geographical placement and/or types of instruments that are employed in gathering data to understand change.

Ultimately, CBO confers several advantages that IDD cannot: (1) it provides locally explicit, culturally based, and social contexts of change which are critical to effective adaptation; (2) it cultivates the sharing of lessons learned among individuals; and (3) it helps sustain livelihoods and human connections to land- and water-scapes. For these reasons, CBO, not only as a science but also as a process, is critical to the suite of tools we use to understand and respond to change in the Arctic, and potentially in other regions of the world.

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References

Achard R, Eva H, Mayaux P (2001) Tropical forest mapping from coarse spatial resolution satellite data: production and accuracy assessment issues. Int J Remote Sens 22(14):2741–2762. https://doi.org/10.1080/01431160120548

Alaska Department of Fish and Game (2012) Subsistence in Alaska: a year 2012 update. http://www.adfg.alaska.gov/index.cfm?ADFG=subsistence.main

Alaska Department of Fish and Game (2016) Subsistence division, Community Subsistence Information System (CSIS). http://www.adfg.alaska.gov/sb/CSIS/index.cfm?ADFG=harvInfo.harvestCommSelComm

Alaska Ocean Observing System (2016) http://portal.aoos.org/real-time-sensors.php#module-search?lg=8c5dd704-59ad-11e1-bb67-0019b9dae22b&p=proj3857&b=google_hybrid&page=1&tagId=&q=chukchi%2Bsea. Accessed 6 July 2016

Alessa LN, Kliskey A, Williams P, Barton M (2008) Perceptions of change in freshwater in remote resource-dependent arctic communities. Glob Environ Chang 18:153–164. https://doi.org/10.1016/j.gloenvcha.2007.05.007

Alessa LN, Kliskey A, Williams P (2010) Forgetting freshwater: technology, values, and distancing in remote arctic communities. Soc Nat Res 23(3):254–268. https://doi.org/10.1080/08941920802454813.

Alessa L, Kliskey A, Drukenmiller M, Griffith D, McKann H, Myers B, Pulsifer P, Beaujean G, Behe C, Jackson L (2016a) Best practices for community-based observing. Moscow, ID: Center for Resilient Communities, University of Idaho. http://www.uidaho.edu/caa/galleries-centers-and-lab/crc/news

Alessa L, Kliskey A, Gamble J, Fidel M, Beaujean G, Gosz J (2016b) The role of indigenous science and local knowledge in integrated observing systems: moving toward adaptive capacity indices and early warning systems. Sustain Sci 11(1):91–102. https://doi.org/10.1007/s11625-015-0295-7.

Alexander C, Bynum N, Johnson E, King U, Mustonen T, Neofotis P, Oettle N, Rosenzweig C, Sakakibara C, Shadrin V, Vicarelli A, Waterhouse J, Weeks B (2011) Linking Indigenous Knowledge and scientific knowledge of climate change. BioScience 61(6): 477–484. https://doi.org/10.1525/bio.2011.61.6.10

Ambrose WG Jr, Clough LM, Johnson JC, Greenacre M, Griffith DC, Carroll ML, Whiting A (2014) Interpreting environmental change in coastal Alaska using traditional and scientific ecological knowledge. Front Mar Sci 1 article 40. https://doi.org/10.3389/fmars.2014.00040

Berger M, Mamdani M, Atkins D, Johnson M (2009) Good research practices for comparative effectiveness research: defining, reporting and interpreting nonrandomized studies of treatment effects using secondary sources. Value Health 12(8):1044–1052. https://doi.org/10.1111/j.1524-4733.2009.00600.x

Berkes F, Colding J, Folke C (2000) Rediscovery of traditional ecological knowledge as adaptive management. Ecol Appl 10(5):1251–1262. https://doi.org/10.1890/1051-0761

Brewster K (2004) The whales they give themselves: conversations with Harry Brower, Sr. University of Alaska Press, Fairbanks

Brubaker MY, Bell JN, Berner JE, Warren JA (2011) Climate change health assessment: a novel approach for Alaska Native communities. Int J Circumpolar Health 70(3):266–273. https://doi.org/10.3402/ijch.v70i3.17820

Clark A (2013) Whatever next? Predictive brains, situated agents, and the future of cognitive science. Behav Brain Sci 35:181–253. https://doi.org/10.1017/S0140525X12000477

Cleveland RB, Cleveland WS, McRae JE, Terpenning I (1990) STL: a seasonal-trend decomposition procedure based on Loess. J Off Stat 6(1):3–73

Collings P (2011) Economic strategies, community, and food networks in Ulukhaktok, Northwest Territories Canada. Arctic 64(2):207–219. https://doi.org/10.14430/arctic4100

Community Observation Network for Adaptation and Security (CONAS) (n.d.) http://conas-ak.org/ . Accessed 6 July 2016

Csavina J, Roberti JA, Taylor JR, Loescher HW (2017) Traceable measurements and calibration: a primer on uncertainty analysis. Ecosphere 8(2):e01683. https://doi.org/10.1002/ecs2.1683

Dickersin K, Berlin J (1992) Meta-analysis: state of the science. Epidemiol Rev 14(1):154–176. https://doi.org/10.1093/oxfordjournals.epirev.a036084

Eicken H, Lee O (2013) Status of current observing system, White Paper Synthesis Brief of the Arctic Observing Summit, Vancouver, BC, Canada. http://www.arcticobservingsummit.org/users/white_papers.php

Eklundh L, Jönsson P (2015) TIMESAT: a software package for time-series processing and assessment of vegetation dynamics. In: Kuenzer C, Dech S, Wagner W (eds) Remote sensing time series. Springer International, pp 141–158. https://doi.org/10.1007/978-3-319-15967-6_7

Fernandez-Llamazares A, Diaz-Reviriego I, Luz AC, Cabeza M, Pyhala A, Reyes-Garcia V (2015) Rapid ecosystem change challenges the adaptive capacity of Local Environmental Knowledge. Glob Environ Chang 31:272–284. https://doi.org/10.1016/j.gloenvcha.2015.02.001

Fienup-Riordan A, Carmack E (2011) The ocean is always changing: nearshore and farshore perspectives on Arctic Coastal Seas. Oceanography 24(3):266–279. https://doi.org/10.5670/oceanog.2011.78

Ford JD, Pearce T (2012) Climate change vulnerability and adaptation research focusing on the Inuit subsistence sector in Canada: directions for future research. Can Geogr 56(2):275–287. https://doi.org/10.1111/j.1541-0064.2012.00418.x

Ford JD, Pearce T, Gilligan J, Smit B, Oakes J (2008) Climate change and hazards associated with ice use in Northern Canada. Arct Antarct Alp Res 40(4):647–649. https://doi.org/10.1657/1523-0430(07-040)[FORD]2.0.CO;2

Frey KE, Moore GWK, Cooper LW, Grebmeier JM (2015) Divergent patterns of recent sea ice cover across the Bering, Chukchi, and Beaufort seas of the Pacific Arctic Region. Prog Oceanogr 136: 32–49. https://doi.org/10.1016/j.pocean.2015.05.009

Gearheard S, Pocernich M, Stewart R, Sanguya J, Huntington HP (2010) Linking Inuit knowledge and meteorological station observations to understand changing wind patterns at Clyde River, Nunavut. Clim Chang 100:267–294. https://doi.org/10.1007/s10584-009-9587-1.

Grebmeier JM (2012) Shifting patterns of life in the Pacific Arctic and Sub-Arctic Seas. Annu Rev Mar Sci 4:63–78. https://doi.org/10.1146/annurev-marine-120710-100926

Gupta SV (2012) Measurement uncertainties: physical parameters and calibration of instruments. Springer-Verlag, Berlin. https://doi.org/10.1007/978–3–642-20989-5

Harris IPDJ, Jones PD, Osborn TJ, Lister DH (2014) Updated high-resolution grids of monthly climatic observations-the CRU TS3.10 Dataset. Int J Climatol 34(3):623–642. https://doi.org/10.1002/joc.3711

Herman-Mercer N, Schuster PF, Maracle KB (2011) Indigenous observations of climate change in the Lower Yukon River Basin, Alaska. Hum Organ 70(3):244–252. https://doi.org/10.17730/humo.70.3.v88841235897071m

Hoffman DD, Prakash C (2014) Objects of consciousness. Front Psychol 5, article 577. https://doi.org/10.3389/fpsyg.2014.00577

Hoffman DD, Singh M, Prakash C (2015) The interface theory of perception. Psychon Bull Rev 22(6):1480–1506. https://doi.org/10.3758/s13423-015-0890-8

Huntington HP, Callaghan T, Fox S, Krupnik I (2004) Matching traditional and scientific observations to detect environmental change: a discussion on arctic terrestrial ecosystems. Ambio Special report #13, 18–23

Huntington HP, Noongwook G, Bond NA, Benter B, Snyder JA, Zhang J (2013) The influence of wind and ice on spring walrus hunting success on St. Lawrence Island, Alaska. Deep Sea Res II Top Stud Oceanogr 94:312–322. https://doi.org/10.1016/j.dsr2.2013.03.016

Jia GJ, Epstein HE, Walker DA (2003) Greening of Arctic Alaska, 1981–2001. Geophys Res Lett 30. http://onlinelibrary.wiley.com/doi/10.1029/2003GL018268/full

Jolly D, Berkes F, Castleden J, Nichols T, the community of Sachs Harbour (2002) We can't predict the weather like we used to. In: Krupnik I, Jolly D (eds) The earth is faster now: indigenous observations of environmental change. Fairbanks, Arctic Research Consortium of the United States 384 pp

Jönsson P, Eklundh L (2002) Seasonality extraction by function fitting to time-series of satellite sensor data. IEEE Trans Geosci Remote Sens 40(8):1824–1832. https://doi.org/10.1109/TGRS.2002.802519

Kane DL, Stuefer SL (2015) Reflecting on the status of precipitation data collection in Alaska: a case study. Hydrol Res 46(4):478–493. https://doi.org/10.2166/nh.2014.023

Karl TR, Williams CN Jr (1987) An approach to adjusting climatological time series for discontinuous inhomogeneities. J Clim Appl Meteorol 26(12):1744–1763. https://doi.org/10.1175/1520-0450(1987)026<1744:AATACT>2.0.CO;2

Klein JA, Hopping KA, Yeh ET, Nyima Y, Boone RB, Galvin KA (2014) Unexpected climate impacts on the Tibetan Plateau: local and scientific knowledge in findings of delayed summer. Glob Environ Chang 28:141–152. https://doi.org/10.1016/j.gloenvcha.2014.03.007

Lavie N, Hirst A, de Fockert JW, Vidding E (2004) Load theory of selective attention and cognitive control. J Exp Psychol Gen 133(3):339–354. https://doi.org/10.1037/0096-3445.133.3.339

Lynch P (2016) 2016 climate trends continue to break records. NASA's Goddard Space Flight Center. http://climate.nasa.gov/news/2465/2016-climate-trends-continue-to-break-records/

Magnuson S (2014) New satellite systems to boost communication coverage in Arctic. National Defense. http://www.nationaldefensemagazine.org/archive/2014/August/pages/NewSatelliteSystemstoBoostCommunicationCoverageinArctic.aspx

Mahoney A, Eicken H, Shapiro L, Gaylord A (2006) Mapping and characterization of recurring spring leads and landfast ice in the Beaufort and Chukchi Seas. Mineral Management Service. AK-03-06, MMS-71707

Marsh ET (2007) Retelling is not the same as recalling: implications for memory. Curr Dir Psychol Sci 16(1):16–20. https://doi.org/10.1111/j.1467-8721.2007.00467.x

Meier WN, Gerland S, Granskog MA, Key JR, Haas C, Hovelsrud GK, Kovacs KM, Makshtas A, Michel C, Perovich D, Reist JD, van Oort BEH (2011) Sea ice. In: Arctic monitoring and assessment programme, snow, water, ice and permafrost in the Arctic (SWIPA): climate change and the cryosphere. Oslo, Norway. xii + 538 pp. Available at http://www.amap.no/documents/doc/arctic-climate-issues-2011-changes-in-arctic-snow-water-ice-and-permafrost/129

National Research Council (2006) Toward an integrated Arctic observing network. http://www.nap.edu/catalog/11607.html

New M, Hulme M, Jones P (2000) Representing twentieth-century space-time climate variability. Part II: Development of 1901–96 monthly grids of terrestrial surface climate. J Clim 13(13):2217–2238. https://doi.org/10.1175/1520-0442(2000)013<2217:RTCSTC>2.0.CO;2

Pachur T, Todd PM, Gigerenzer G, Schooler LJ, Goldstein DG (2012) When is the recognition heuristic an adaptive tool? In: Todd PM, Gigerenzer G (eds) Ecological rationality: intelligence in the world. Oxford University Press, New York, pp 113–143

Pattison RR, Jorgenson JC, Raynolds MK, Welker JM (2015) Trends in NDVI and tundra community composition in the Arctic of northeast Alaska between 1984 and 2009. Ecosystems 18(4):707–719. https://doi.org/10.1007/s10021-015-9858-9

Pearce TD, Ford JD, Laidler GJ, Smit B, Duerden F, Allarut M, Andrachuck M, Baryluk S, Dialla A, Elee P, Goose A, Ikummaq T, Joamie E, Kataoyak F, Loring E, Meakin S, Nickels S, Shappa K, Shirley J, Wandel J (2009) Community collaboration and climate change research in the Canadian Arctic. Polar Res 28:10–27. https://doi.org/10.1111/j.1751-8369.2008.00094.x

Prno J, Bradshaw B, Wandel J, Pearce T, Smit B, Tozer L (2011) Community vulnerability to climate change in the context of other exposure-sensitivities in Kugluktuk, Nunavut. Polar Res 30:7363. https://doi.org/10.3402/polar.v30i0.7363

Raichlan DA, Wood BM, Gordon AD, Magulla AZP, Marlowe FW, Pontzer H (2014) Evidence of Lévy walk foraging patterns in human hunter-gatherers. Proc Natl Sci Acad 111(2):728–733. https://doi.org/10.1073/pnas.1318616111

Ramnath A (2014) 'Indigenous Knowledge' and 'Science' in the age of globalization. IIM Kozhikode Soc Manag Rev 3(1):101–107. https://doi.org/10.1177/2277975214532180

Robards MD, Kitaysky AS, Burns JJ (2013) Physical and sociocultural factors affecting walrus subsistence at three villages in the northern Bering Sea: 1952–2004. Polar Geogr 36(1–2):65–85. https://doi.org/10.1080/1088937X.2013.765519

Russian Census (2010) https://en.rian.ru/infographics/20111222/170405728.html

Sand Point, Alaska (2014) http://www.sandpointak.com/

Shimada K, Kamoshida T, Itoh M, Nishino S, Carmack E, McLaughlin F, Zimmermann S, Proshutinsky A (2006) Pacific Ocean inflow: influence on catastrophic reduction of sea ice cover in the Arctic Ocean. Geophys Res Lett 33(8): (L08605). https://doi.org/10.1029/2005GL025624

Smith DA, Vodden K, Woodrow M, Khan A, Furst B (2014) The last generation? Perspectives of inshore fish harvesters from Change Islands, Newfoundland. Can Geogr 58(1):95–109. https://doi.org/10.1111/j.1541-0064.2013.12053.x

Stefanucci JK, Proffitt DR (2009) The roles of altitude and fear in the perception of height. J Exp Psychol Hum Percept Perform 35(2):424–439. https://doi.org/10.1037/a0013894

Stow D, Daeschner S, Hope A, Douglas D, Petersen A, Myneni R, Zhou L, Oechel W (2003) Variability of the seasonally integrated normalized difference vegetation index across the north slope of Alaska in the 1990s. Int J Remote Sens 24(5):1111–1117. https://doi.org/10.1080/0143116021000020144

Stroeve J, Serreze M, Holland M, Kay J, Melanik J, Barrett A (2012) The Arctic's rapidly shrinking sea ice cover: a research synthesis. Clim Chang 110:1005–1027. https://doi.org/10.1007/s10584-011-0101-1

Stroeve JC, Markus T, Boisvert L, Miller J, Barrett A (2014) Changes in Arctic melt season and implications for sea ice loss. Geophys Res Lett 41(4):1216–1225. https://doi.org/10.1002/2013GL058951

United Nations (2008) United Nations Declaration on the Rights of Indigenous Peoples. Resolution adopted by the General Assembly, March 2008. United Nations

United States Census, American FactFinder (2010) http://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

Verbyla D (2008) The greening and browning of Alaska based on 1982–2003 satellite data. Glob Ecol Biogeogr 17(4):547–555. https://doi.org/10.1111/j.1466-8238.2008.00396.x

Weatherhead E, Gearheard S, Barry RG (2010) Changes in weather persistence: insight from Inuit Knowledge. Glob Environ Chang 20(3):523–528. https://doi.org/10.1016/j.gloenvcha.2010.02.002

Wentz FJ, Matthias S (2000) Precise climate monitoring using complementary satellite data sets. Nature 403(27):414–416. https://doi.org/10.1038/35000184

Witt JK, Dorsch TE (2009) Kicking to bigger uprights: field goal kicking performance influences perceived size. Perception 38(9):1328–1340. https://doi.org/10.1068/p6325

Woodgate RA, Weingartner T, Lindsay R (2010) The 2007 Bering Strait oceanic heat flux and anomalous Arctic Sea-ice retreat. Geophys Res Lett 37:L01602. https://doi.org/10.1029/2009GL041621

Xiong X, Sun J, Barnes W, Salomonson V, Esposito J, Erives H, Guenther B (2007) Multiyear on-orbit calibration and performance of Terra MODIS reflective solar bands. IEEE Trans Geosci Remote Sens 45(4):879–889. https://doi.org/10.1109/TGRS.2006.890567

Zak A (2016) This luxury cruise ship will soon sail through the Arctic. Here's what that means for Alaska. The Alaska Dispatch News. http://www.adn.com/arctic/2016/06/12/this-luxury-cruise-ship-will-soon-sail-through-the-arctic-heres-what-that-means-for-alaska/