Influence of statistical methods and reference dates on describing temperature change in Alaska

Christopher Bone,[1] Lilian Alessa,[1] Andrew Kliskey,[1] and Mark Altaweel[2]

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[1] Quantifying temperature trends across multiple decades in Alaska is an essential component for informing policy on climate change in the region. However, Alaska's climate is governed by a complex set of drivers operating at various spatial and temporal scales, which we posit should result in a sensitivity of trend estimates to the selection of reference start and end dates as well as the choice of statistical methods employed for quantifying temperature change. As such, this study attempts to address three questions: (1) How sensitive are temperature trend estimates in Alaska to reference start dates? (2) To what degree do methods vary with respect to estimating temperature change in Alaska? and (3) How do different reference start dates and statistical methods respond to climatic events that impact Alaska's temperature? To answer these questions, we examine the use of five methods for quantifying temperature trends at 10 weather stations in Alaska and compare multiple reference start dates from 1958 to 1993 while using a single reference end date of 2003. The results from this analysis demonstrate that, with some methods, the discrepancy in temperature trend estimates between consecutive start dates can be larger than the overall temperature change reported for the second half of the 20th century. Second, different methods capture different climatic patterns, thus influencing temperature trend estimates. Third, temperature trend estimation varies more significantly when a reference start date is defined by an extreme temperature. These findings emphasize that sensitivity analyses should be an essential component in estimating multidecadal temperature trends and that comparing estimates derived from different methods should be performed with caution. Furthermore, the ability to describe temperature change using current methods may be compromised given the increase in temperature extremes in contemporary climate change.

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1. Introduction

[2] Estimating temperature trends has become an integral component in the development of government policies due to the need to mitigate and adapt to the purported environmental and social impacts of climate change. In Alaska, for example, observed warming trends over the 20th century have led to the degradation of freshwater resources and infrastructure due to changes in permafrost regimes in specific areas of the state [*White et al.*, 2007]. This has resulted in the formation of state-level committees in Alaska that are responsible for utilizing temperature trend estimations in policy decision making [*AAG*, 2010]. Among several challenges within this process is determining suitable means of detecting and quantifying multidecadal temperature trends in Alaska.

[3] The climate in Alaska is driven by multiple factors, including a highly variable topography, proximity to oceans, the presence of multiple pressure systems, and the impacts of cyclical climatic events [*Benson et al.*, 1983; *Stafford et al.*, 2000; *Polyakov et al.*, 2003]. The Siberian high and the Arctic high-pressure systems impact daily temperatures in the north and the interior, while the Aleutian low influences daily temperatures in the south and west [*Martyn*, 1992; *Overland et al.*, 1999]. At longer time scales the El Niño–Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) can have significant implications for temperature across the state [*Bond and Harrison*, 2006; *Masuda et al.*, 2006; *Combes and Di Lorenzo*, 2007]. ENSO, a tropical Pacific atmosphere-ocean phenomenon with global climatic impacts, is responsible for the 1–2 year El Niño and La Niña events that lead to, broadly speaking, changes in heat transfer from tropical to higher latitudes in both hemispheres [*McLean et al.*, 2009]. During El Niño winters a more persistent flow exists from the North Pacific

[1]Resilience and Adaptive Management Group, University of Alaska Anchorage, Anchorage, Alaska, USA.
[2]University of Chicago Computation Institute, Chicago, Illinois, USA.

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into Alaska, resulting in warmer winters across most of the state [*Graham*, 1994; *Renwick and Wallace*, 1996]. At even longer time scales the PDO represents a 20–30 year cycle between warm and cool sea surface temperatures (SSTs) in the North Pacific [*Papineau*, 2001]. The change between warm and cool SSTs can occur over relatively short time periods and lead to dramatic change in temperatures [*Mantua et al.*, 1997; *Chavez et al.*, 2003].

[4] The existence of both short- and long-term climatic cycles and patterns, and the interplay between them, requires that specific attention be paid to the way in which temperature trends are identified and described. This includes the choice of appropriate dates of reference from which to start and end temperature trend estimations as well as the type of statistical method that is employed. The choice of reference dates can lead to biases in temperature trend estimations, as climatic events or temperature anomalies can skew statistical means or cause a disproportionate influence when estimating trend lines. For example, estimating multidecadal temperature trends in Alaska with a linear best-fit model was shown to be heavily biased by the reference dates owing to the presence of the PDO. *Hartman and Wendler* [2005] demonstrate that observed increases in temperature across Alaska between 1951 and 2001 can also be observed as temperature declines when taking the 1976 PDO event into consideration by estimating, instead, trends within the period 1951–1975 and within the period 1977–2001.

[5] The choice of statistical method also contributes to biases in trend estimation due to the window of values used in estimation and how these values are treated. Some methods, such as a running mean that is implemented for smoothing data, are considered local statistics that estimate average temperatures by sampling relatively few sequential observations. It is argued that smoothing time series data are inherently subjected to boundary conditions (i.e., the start and end of the trend), which has prompted the emergence of methods for handling such constraints [*Folland et al.*, 2001; *Mann*, 2004]. However, such methods have been deemed subjective and should be avoided in order to communicate accurate information regarding temperature trends [*Soon et al.*, 2004]. Furthermore, the selection of a window size (i.e., the numbers of values incorporated in estimating a running mean) can also impact trend estimations, as too small a window can be overinfluenced by anomalies, while too large a window can negate the ability to detect natural cyclical variation in the data. Alternatively, global statistics can be employed for utilizing all values in a time series. The linear-fit model based on least-square regression, for example, is employed for estimating temperature trends in Alaska [*Hartmann and Wendler*, 2005; *Wendler and Shulski*, 2009]. While such methods avoid the issue of selecting window size, the use of a linear best-fit line can overlook local variation that is captured by more localized methods.

[6] In reporting temperature trends in Alaska it is therefore imperative to understand how the selection of reference dates and statistical methods influence the overall trend estimation. This study proposes to address the following questions in the context of temperature change in Alaska: (1) How sensitive are temperature trend estimates to reference start dates (RSDs)? (2) To what degree do methods vary with respect to estimating temperature change? and (3) How do different RSDs and statistical methods respond to climatic events that impact Alaska's temperature? In doing so we intend to lend insight into how the decisions surrounding methods for understanding temperature trends can impact broader policies on climate change.

2. Data and Methodology

[7] Temperature recordings from 10 climate stations across Alaska were used to address the questions of this study. The specific climate stations were selected to ensure that each climate region in Alaska, as defined by *Hartmann and Wendler* [2005], is represented. The location of each station is shown in Figure 1. Average annual temperatures at each station are shown for the time period between 1958 and 2003 in Figure 2. The data were collected from the Alaska Climate Research Center at the University of Alaska Fairbanks (Climatological data—Monthly time series; available at http://climate.gi.alaska.edu).

[8] Five statistical methods were employed to describe temperature change: (1) a 5-year running average, (2) a 10-year running average, (3) a 5-year Hamming filter, (4) a 10-year Hamming filter, and (5) a linear best-fit model. The Hamming filter method, employed by *IPCC* [2003] for estimating global temperature trends, uses a neighborhood function that weights observations based on their location within the window. It is similar to a running average in that a set of observations is used to estimate the average temperature at a specific date, but observations farther from the date being estimated have less influence. A weight, w, for each data point, i, is calculated by

$$w(i) = 0.54 - 0.46\cos[2\pi i(n-1)], \quad (1)$$

where n is the length of the window. The selection of these five methods was based on the need to compare local and global methods, to determine the influence of different window sizes for smoothing data sets, to evaluate how filters impact smoothing procedures, and to use accepted methods in estimating temperature change.

[9] The five methods were employed using different RSDs, ranging between 1958 and 1993, and a single end date of 2003. These dates were selected based on methodological requirements and data availability; owing to the intent of this study to investigate the sensitivity of various methods, it is important that the data set be composed of complete temperature records (i.e., a temperature record exists for each month) for all 10 climate stations and that no additional modifications to the estimates, such as padding [see *Soon et al.*, 2004], be performed. The complete data record for 10 stations at the time of this study existed for the period between 1953 and 2008. However, because this study employed a 10 year running mean and 10 year Hamming filter, the actual period evaluated has shortened by 5 years at the beginning and at the end, resulting in an analysis period between 1958 and 2003.

3. Results

3.1. How Sensitive Are Temperature Trend Estimates to Reference Dates?

[10] The estimated temperature between the RSDs and 2003 for all statistical methods are displayed in Figure 3. All

Figure 1. Location of the 10 climate stations in Alaska.

weather stations, regardless of the method employed, demonstrate a trend of increasing temperatures between 1958 and 2003. This is consistent with global temperature trends [*IPCC*, 2007] and trends reported for Alaska [*AAG*, 2010]. However, the graphs in Figure 3 also demonstrate that estimates are highly dependent on the RSD that is used, as, for some methods, temperature trend estimations can vary as much as 4°C when using different RSDs. This is particularly evident when observing the 5 year Hamming filter estimations for Anchorage, Barrow, Fairbanks, King Salmon, Kotzebue, McGrath, Nome, and Yakutat. The significant discrepancy in estimates is dependent on the method employed, but even the most conservative variation between estimates for any site is 1.71°C (see the 10 year running mean for St. Paul). Discrepancies in estimates are expected over decades in Alaska owing to the observed warming temperatures; however, such discrepancies should then exhibit a pattern of gradually declining temperature change estimates. That is, temperature change estimates should be higher when using 1958 for an RSD, then gradually decline until the RSD of 1993. The Barrow weather station is the only station that appears to consistently show declining temperature trend estimates with the exception of minor variations. This may result from the fact that Barrow's location in the Arctic, as opposed to the subarctic location of the other stations, puts it at a greater distance from the Pacific Ocean, with intervening topography and prevailing winds that potentially make it less susceptible to climate systems originating in the Pacific Ocean.

[11] The most notable distinction in the RSDs is the change from positive to negative temperature trends in the mid-1970s. With the exception of Barrow and McGrath, all weather stations exhibit a shift from estimates that use an RSD between 1958 and 1973 to a decrease when using an RSD from the mid-1970s. This shift from positive to negative trends coincides with the 1976 Pacific Climate Shift as described by *Hartman and Wendler* [2005]. This shift led to higher-than-average temperatures for most stations starting in 1976, which continued for a varying number of years depending on the weather station's location. As a result, the temperatures in the remaining part of the time series are lower than the temperatures during the shift, which manifests in a negative temperature trend.

[12] The filled circles in Figure 3 indicate the year in which the difference from the previous year in temperature trend estimation is most significant; that is, which consecutive years demonstrate the greatest variation in estimating temperature change. Figure 3 demonstrates that the difference between some consecutive RSDs is greater than the overall temperature change estimation. Examples of this finding include Yakutat, where the temperature change estimate between 1958 and 2003 using the 5 year running mean is 0.53°C, and the 5-year Hamming filter estimate is 0.15°C. These estimates can be compared to the year-to-year discrepancies in the respective graphs that are highlighted by the filled circles. Thus, the combination of certain RSDs and methods can lead to a variation in temperature trend estimates that is greater from one year to the next than is the estimated temperature change over the entire second half of the 20th century.

3.2. To What Degree Do Methods Vary with Respect to Estimating Temperature Change in Alaska?

[13] The five statistical methods display notable differences in their estimations of temperature trends. The bar graphs in Figure 3 reveal a discrepancy between the local and the global methods regarding the relative RSD for which temperature change is most significant. The linear

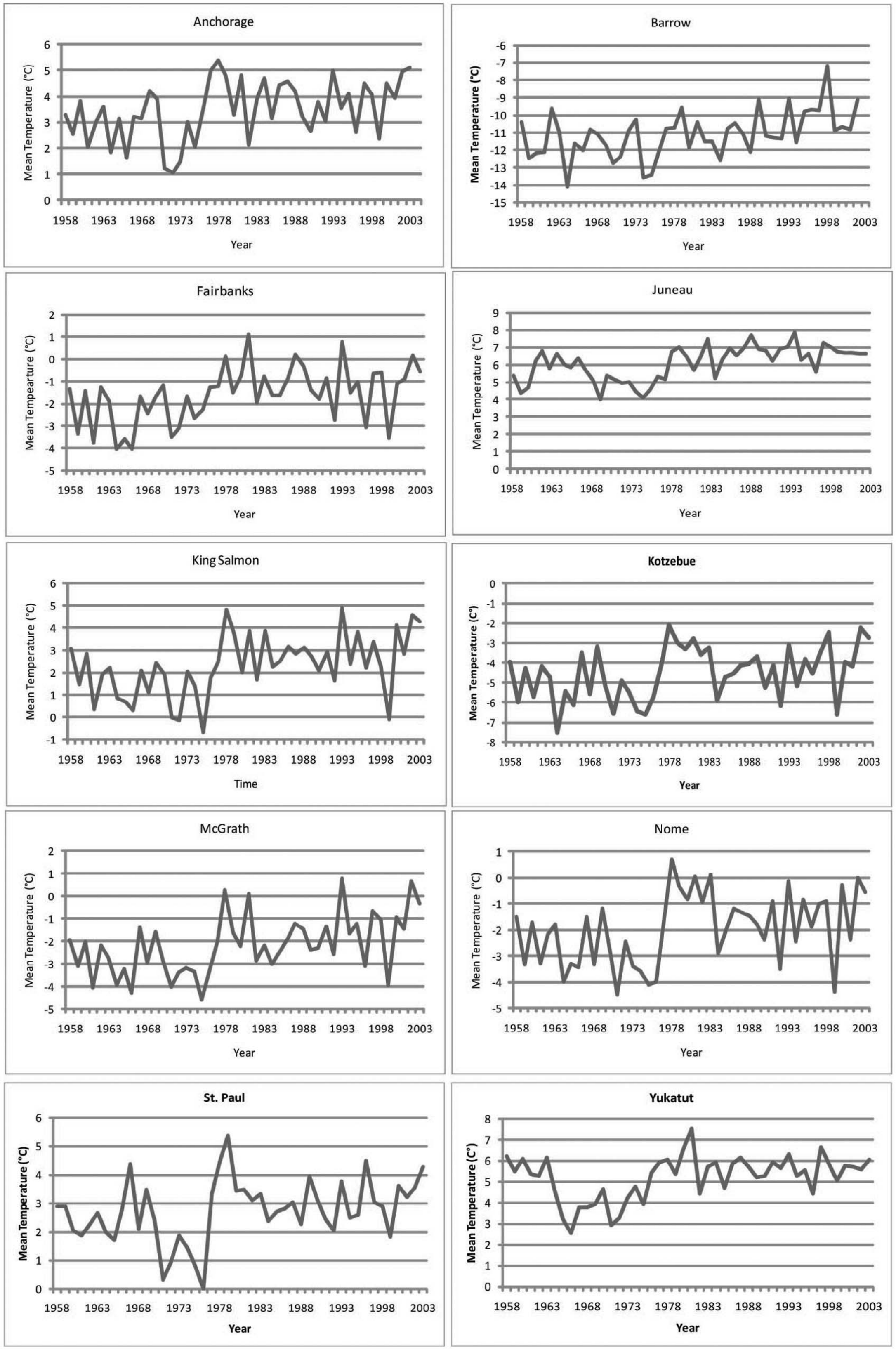


Figure 2. Annual average temperatures from 1958 to 2003 for each weather station. Note that the scale on the y-axis differs for each graph.

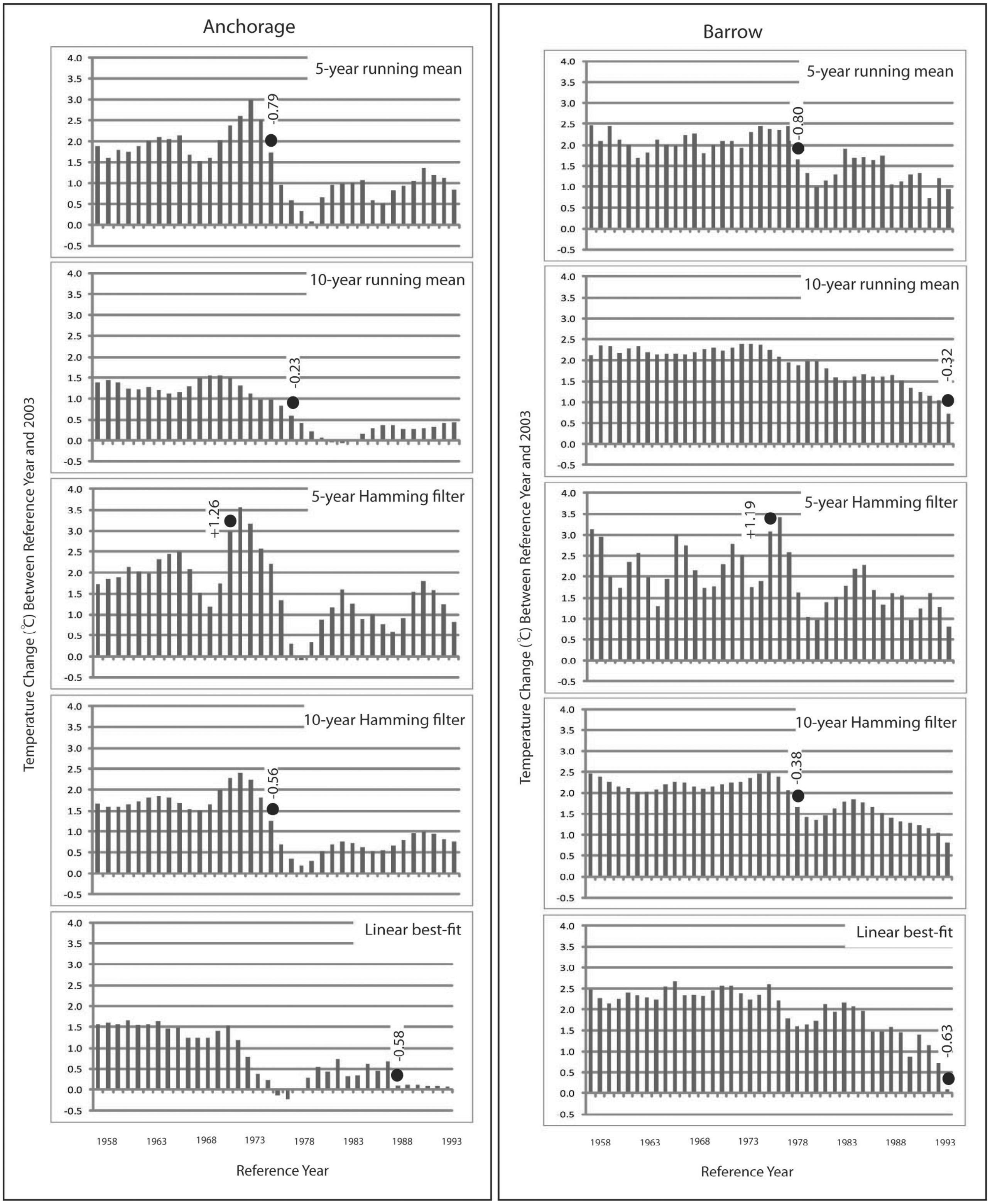


Figure 3. Estimated temperature change between the reference start date (RSD) year and 2003 for the five methods. The filled circle represents the RSD in which the estimate differs most from the previous year.

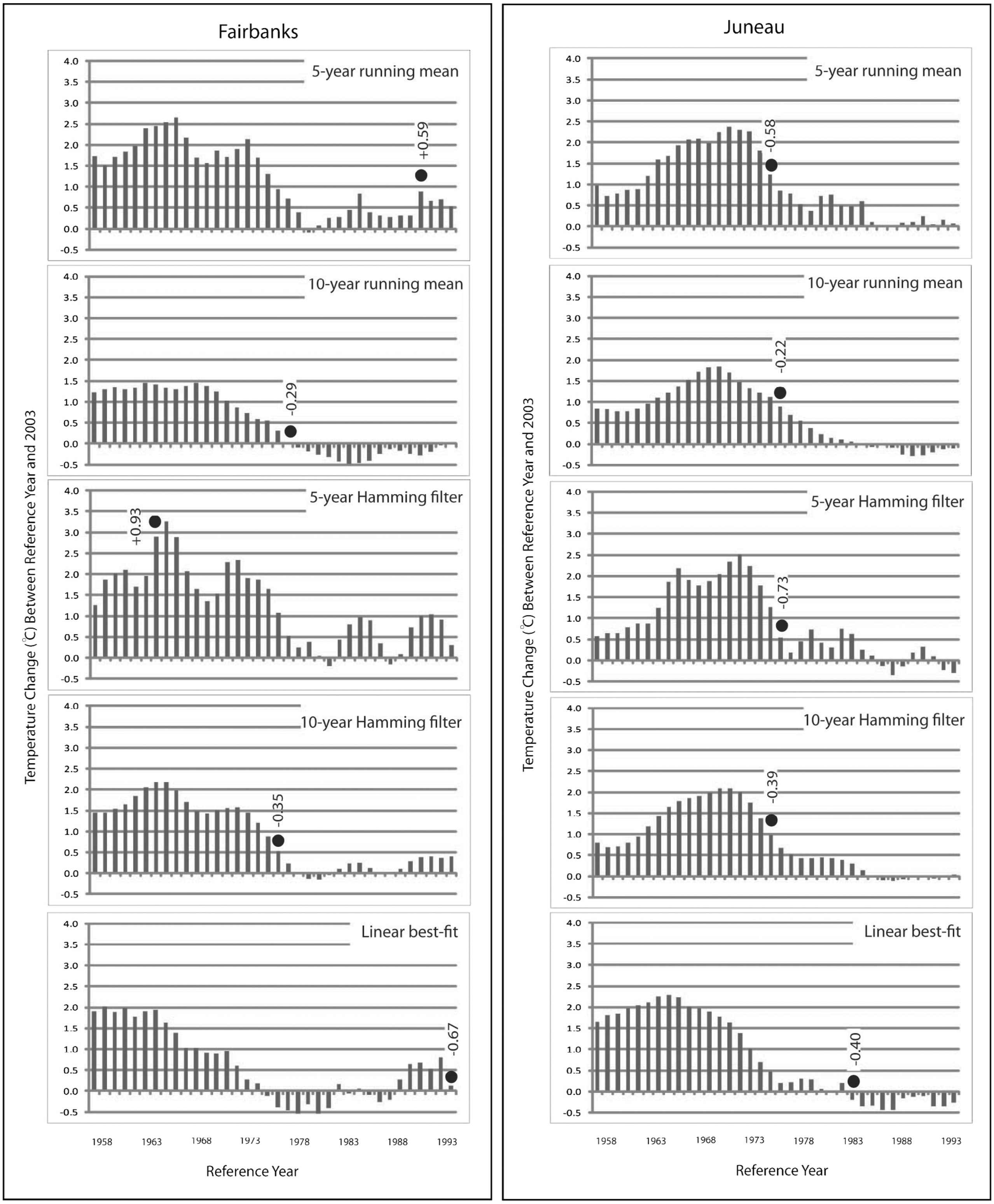
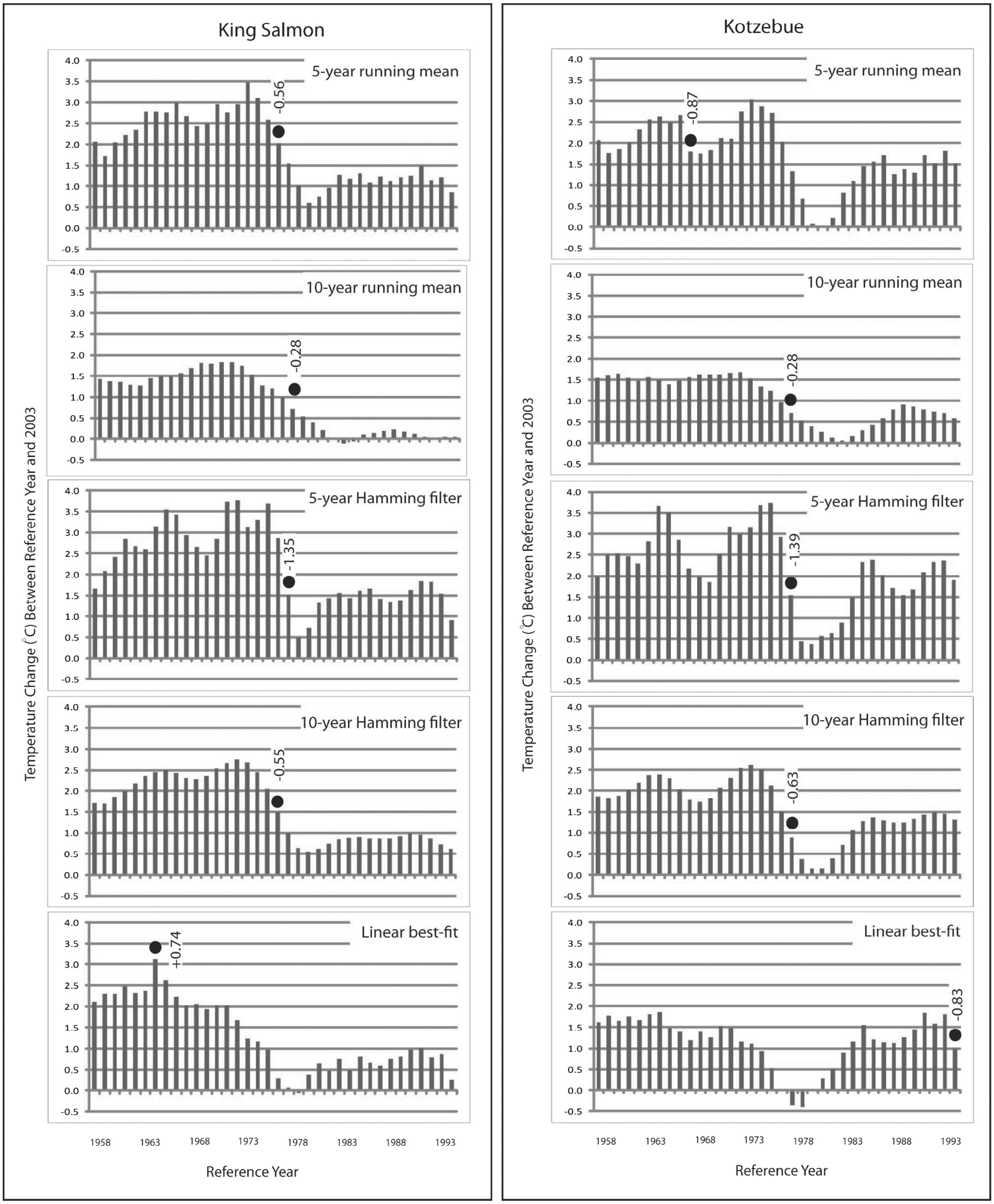


Figure 3. (continued)

best fit typically estimates the greatest temperature change occurring when employing RSDs from early in the time series, particularly for Anchorage, Fairbanks, King Salmon, Kotzebue, McGrath, Nome, and Yakutat. For the local methods the highest estimates of temperature change typically occur when using RSDs in the few years preceding the PDO shift: years that exhibit cooler than average temperatures. These cool temperatures lead to lower-than-average



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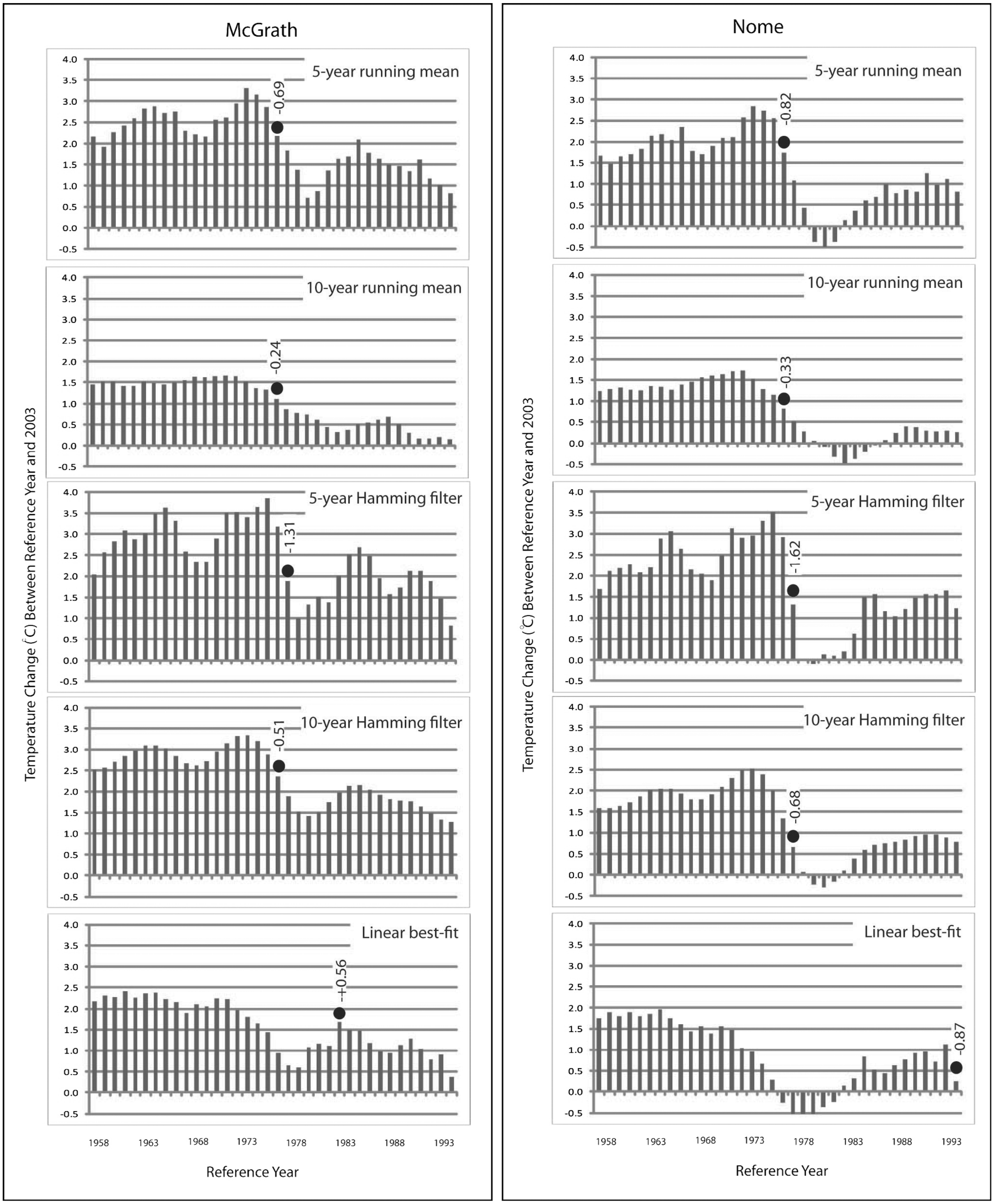
temperature estimates and, hence, greater temperature change from the RSD to 2003. The linear best-fit method is not as sensitive to these cool temperatures because it takes all observations in the time series into account, thus the relatively cool and warm temperatures occurring immediately before and after the PDO shift, respectively, are averaged to produce a moderate amount of temperature change. The one exception to this observation is St. Paul, which is located farther west than the other climate stations and has the closest proximity to the Pacific Ocean. As a



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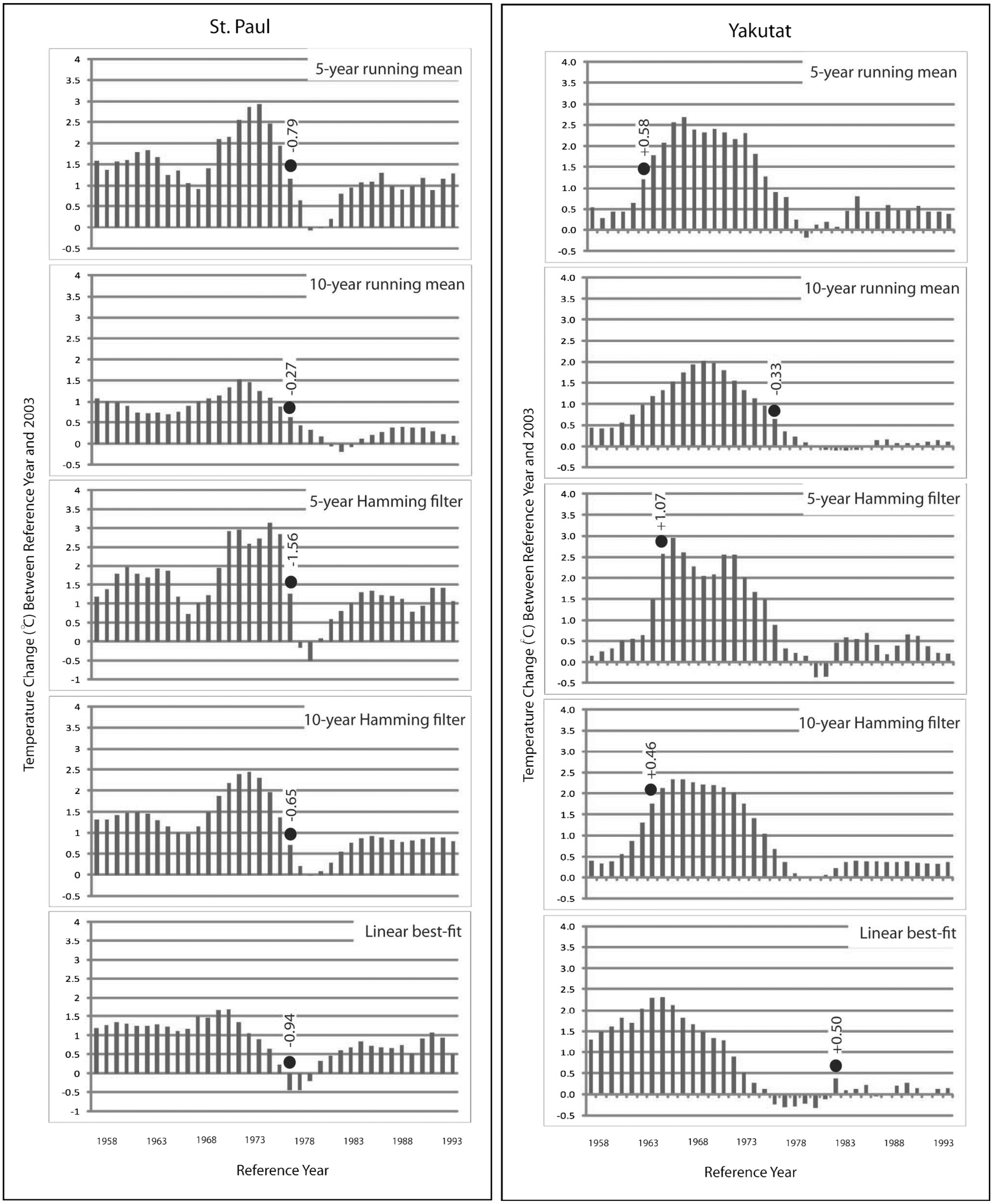
result, the impacts of the PDO on temperatures may have been more significant in this location such that both local and global methods are sensitive to this event.

[14] With regard to the amount of variation between RSDs for each method, the 5-year Hamming filter produces the greatest variation for all dates between 1958 and 1993, as well as the most significant variation between consecutive dates. This finding is due to the fact that the 5 year Hamming filter provides the least amount of smoothing of the four local methods, as it diminishes the influence of data



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points that are closer to the window boundary. As such, the trend estimation is more susceptible to variation in year-to-year temperature observations, especially when involving extreme values. The 5 year running mean also displays notable variation among all estimations and between consecutive year estimations, but not as significant as the Hamming filter, owing to the lack of declining weights. The 10 year running mean and 10 year Hamming filter demonstrate a much less variable set of estimates owing to the enhanced smoothing produced by the inclusion of additional

Table 1. Coefficient of Correlation (r) Values for Comparing Similarity in Temperature Change Estimates Among the Five Methods

	5 Year Running Mean	10 Year Running Mean	5 Year Hamming Filter	10 Year Hamming Filter	Linear Best Fit
5 year running mean	1.00	0.79	0.93	0.95	0.68
10 year running mean		1.00	0.69	0.84	0.78
5 year Hamming filter			1.00	0.91	0.64
10 year Hamming filter				1.00	0.78
Linear best-fit					1.00

values in calculating the mean. However, the 10 year running mean may oversmooth the time series, as the temperature change estimations are lower (in some cases significantly lower) than for all other methods. The linear best-fit model displays a relatively moderate amount of variation between estimates. This method takes all observations into account, thus reducing the sensitivity of year-to-year variation that causes significant variation among the 5 year methods.

[15] Table 1 reports the coefficient of correlation values for each pair of methods. The values in the table reveal that, on the whole, the linear best fit is the least correlated with all the methods, compared to the other four methods, which should be expected given their distinction between local and global methods. The method that appears least different among all methods is the 10 year Hamming filter. This method can thus be seen as one that produces moderate estimates within the context of the tested methods owing to the fact that it is able to capture some of the local variation in the time series while not being overly sensitive to year-to-year temperature differences. The 5 year running mean shares the highest coefficient of correlation with the10 year Hamming filter, owing to the fact that, for the latter, the temperature observations at the edges of the window receive relatively little weight and are thus less instrumental in the derived estimate. The 5 year Hamming filter, which is the most sensitive to year-to-year variation, and the 10 year running mean, which provides the highest degree of smoothing, share the lowest coefficient of correlation value.

3.3. How Do Different Reference Start Dates and Statistical Methods Respond to Climatic Events That Impact Alaska's Temperature?

[16] The range and standard deviation of the different methods for each year are displayed in Figure 4. While the standard deviation remains relatively constant, the range of trend estimates varies significantly from year to year. These results are shown in comparison to the Oceanic Niño Index (ONI), a measurement standard used by the National Oceanic and Atmospheric Association (NOAA) for identifying El Niño (warm) and La Niña (cool) events based on 3 month SST observations in a region in the tropical Pacific (i.e., 5°N–5°S, 120°–170°W). A warm event is considered to take place at five consecutive months above 0.5°C (El Niño),

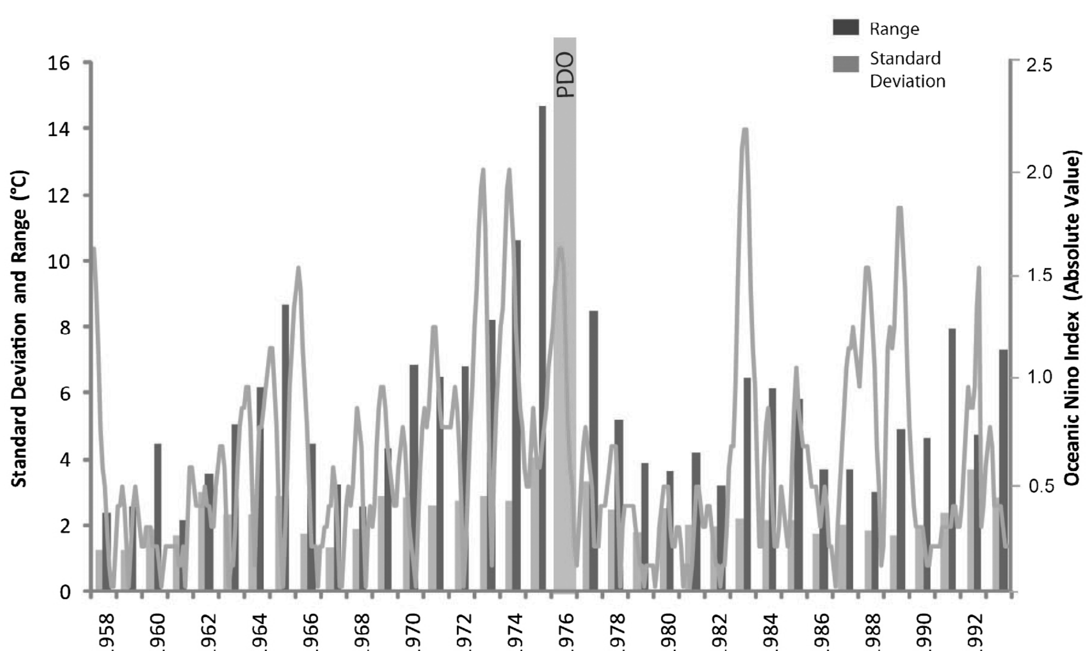

Figure 4. Standard deviation (light gray bar) and range (dark gray bar) of the temperature change estimates provided by the five methods for each RSD (left axis), and the Oceanic Pacific Index (right axis). Timing of the Pacific Decadal Oscillation (PDO) shift is shown.

while a cold event is defined by five consecutive months below −0.5°C (La Niña). Figure 4 displays absolute ONI values to provide a comparison of the range and standard deviation among the five statistical methods.

[17] Figure 4 depicts a strong relationship between ONI values and the range of temperature trend estimates for the majority of years between 1958 and 1993. That is, temperature change estimates exhibit the greatest variation when using an RSD that is defined by a year in which temperatures are abnormally warm or cool and exhibit the greatest similarity during years when temperatures are more moderate. This relationship becomes less significant after the 1980s, suggesting that another climatic pattern may be influencing the discrepancy between temperature trend estimations. However, the signal is significant between 1958 and 1986, revealing that at least some methods are sensitive to temperature extremes resulting from climatic events. This is emphasized by the fact that the greatest range between estimates occurs in 1975, right before the Pacific Climate Shift as measured by the PDO (Figure 4).

[18] In addition, the locations of the filled circles in each graph in Figure 3 display a notable trend when comparing the different methods. For the four local methods 80% of the circles lie on or close to the PDO shift in the mid-1970 s, while for the linear best fit, 40% of the circles occur in 1993 and 30% of the circles occur between 1982 and 1983. Assuming that the filled circles represent sensitivity toward climatic events, this finding reveals that local and global scales capture different types of climatic patterns and anomalies, suggesting that caution is needed when comparing estimates from these different classes of methods.

4. Conclusion

[19] An investigation of the influence of reference dates and statistical methods reveals the inherent sensitivities of temperature trend estimates in Alaska. The selection of reference dates that bound a time series can significantly affect our understanding of temperature change. Depending on the use of some methods, the estimate variation between consecutive years is greater than the overall change in temperature over the second half of the 20th century. Sensitivity analysis thus becomes an important component of the temperature trend estimate process because it can highlight whether using specific reference dates lead to biases. Instead of defining the boundaries of time series on the availability of data, special attention should be given to determining which reference dates in combination with selected statistical procedures produce the least variation from surrounding years. The information presented in Figure 3 could be a potential starting point for a sensitivity analysis, as it reveals the discrepancies in year-to-year temperature change estimates as well as the variation within the entire time series. Such information can be associated with climatic events to determine which dates are more representative of temperature observations from a given time period and which dates are anomalies that can impose significant bias in the temperature trend estimate.

[20] The selection of statistical method also requires much consideration when estimating temperature change over any given time period, owing to the fact that the choices between local and global methods, of window size, and of filters used impact the ability of methods to detect temperature anomalies versus natural cyclical patterns that govern Alaska's climate. It is important to identify whether potential methods can capture trends in the data set while not being overly sensitive to variation. Furthermore, the variation among the methods investigated in this study highlights the need for caution when comparing temperature trends from different studies that use different methods.

[21] Finally, this study reveals that statistical methods provide more variable temperature trend estimates when the RSD is defined by a year that experienced a temperature extreme. This finding, demonstrated by the relationship between the range of estimates and the ONI, has significant repercussions owing to observations of increasing temperature extremes as a result of contemporary climate change [*Easterling et al.*, 2000; *Meehl and Tebaldi*, 2004; *Schar et al.*, 2004]. A more variable climate in Alaska will lead to greater sensitivity of temperature trend estimates to RSDs and, thus, greater discrepancy in reported temperature change among different statistical methods. This has profound implications for management practices that rely on historical trend estimates or that need to anticipate temperature trajectories. Thus, policies are more likely to be effective if greater consideration is given to the ways in which we estimate temperature change.

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L. Alessa, C. Bone, and A. Kliskey, Resilience and Adaptive Management Group, University of Alaska Anchorage, 3101 Science Circle Drive, Room 201D, Anchorage, AK 99508, USA. (afceb@uaa.alaska.edu)

M. Altaweel, University of Chicago Computation Institute, 5640 South Ellis Avenue, Chicago, IL 60637, USA.