7.8 CHANGES IN NORTH AMERICAN EXTREMES DERIVED FROM DAILY WEATHER DATA

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1. INTRODUCTION: WHY EXTREMES ARE IMPORTANT

Most societal infrastructures, as well natural and agricultural plant and animal communities, have little difficulty accommodating moderate changes in typical weather. But changes in the tails of the distribution may not be so easily accommodated because weather extremes often have very direct impacts. For example, extremely hot weather can cause railroad tracks to buckle (Peterson et al., 2006) and adverse human health effects which can involve thousands of fatalities even in developed countries (Karl and Knight, 1997; Schär and Jendritzky, 2004; Milligan, 2005). Cold outbreaks after the start of the growing season have been documented to cause the extinction of local populations of Edith's Checkerspot butterfly (Easterling et al., 2000) as well negatively impacting agricultural production. Weather extremes causing high egg temperatures during the pre-incubation period limit the southern range of the pheasant (Schulte and Porter, 1974). Overwintering insects must avoid injury and death from the freezing of tissues and from metabolic disruptions associated with exposure to low, non-freezing temperatures (Turnock and Fields, 2005). Metabolic disruptions may be due to long periods of moderate cold but the freezing of tissue, which occurs at the supercooling point, is directly related to cold extremes (the supercooling point varies with insect species and is, for example, -15.4°C for Japanese pine sawyer larvae in winter; Ma et al., 2006).

Light snow conditions can slow transportation but blizzards bring air and highway travel to a standstill. Highway underpasses can safely accommodate moderate precipitation, but heavy precipitation may cause flooding. Heavy rain also causes much more severe erosion than moderate rainfall and can lead to increased cases of diarrhea or even outbreaks of cholera in poor countries (Cazelles and Hales, 2006). According to INFEST (1998), spruce bark beetle outbreaks in Alaska are controlled by a combination of predation (woodpeckers), climate (wet, cool springs; extremely cold, snowless winters), and food supply (they "run-out" of large diameter trees; beetle brood production is poor in small diameter trees). When beetle outbreaks spreads, large swaths of forest can die. The standing dead timber, in turn, is a wildfire risk. Therefore, in certain situations, a decrease in winter cold extremes can lead to a serious increase in summer forest fires. In sum, as these examples indicate, extreme weather has profound effects on human and natural systems. Therefore, it is important to understand how extremes are changing within a region such as North America.

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2. HISTORICAL DAILY DATA

Daily maximum temperature (Tmax), minimum temperature (Tmin) and precipitation were analyzed for the stations in Figure 1. Figure 2 shows how the number of stations with data complete enough to calculate indices changed over the analysis period. These daily data are being made available through the North American Extremes Monitoring web page at NOAA's National Climatic Data Center (http://www.ncdc.noaa.gov/nacem/nacem.html).

Figure 1. Locations of meteorological stations whose observations were used in the analyses.

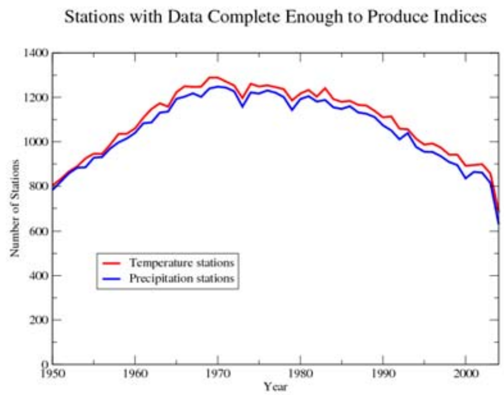

Figure 2. Number of stations with data complete enough to produce indices through time.

2.1 *Canadian data*

Canadian temperature data consist of homogeneity adjusted daily minimum and maximum values for 210 high quality (i.e., few missing values, minimal urban effects), relatively evenly distributed stations across the country. For these data, homogeneity problems caused by station relocation and changes to instrumentation and observing practices have been addressed using a regression technique and surrounding stations (Vincent 1998). Adjustment factors for monthly mean temperatures were computed for identified inhomogeneities. They were further interpolated into daily adjustment factors that were used to obtain the adjusted daily temperatures (Vincent et al. 2002). This dataset has been used in previous studies on changes in Canadian temperature extremes (Bonsal et al., 2001; Vincent and Mekis, 2006).

Canadian precipitation data include adjusted daily rainfall and snowfall amounts observed at 495 stations across the country (Mekis and Hogg, 1999; updated). All known inhomogeneities in the station data caused by changes in the measurement programs were carefully minimized. Wind undercatch, wetting loss, evaporation, trace events, and varying snow densities were also considered in the adjustment procedure. Inhomogeneity due to station relocation was not addressed. A subset of this dataset was used to investigate changes in heavy precipitation events in Canada (Zhang et al., 2001) and trends in precipitation intensity in Canada (Stone et al., 2000).

2.2 *U.S. data*

For the U.S. and Mexico, homogeneity adjusted daily datasets are not yet available. Instead great care was taken to identify any station time series with discontinuities and remove them from the analysis. The U.S. daily data were extracted from the Global Historical Climatology Network (GHCN) Daily dataset (http://www1.ncdc.noaa.gov/pub/data/ghcn/daily/). The U.S. subset of GHCN-Daily is from the National Weather Service Cooperative and First Order weather observing station observations which have undergone quality control at the NOAA's National Climatic Data Center. GHCN-Daily provides a few additional quality control checks. Unfortunately, data from many of these stations are inhomogeneous due to changes in observing location, time of day the observations were made, etc.

To limit the impact of inhomogeneities on the analyses several steps were taken. First, no data prior to 1950 were used as longer time series have greater chance of containing artificial discontinuities and stations with short time series were removed from the analysis as well. Then the data for the contiguous United States (CONUS) were subjected to statistical tests by Menne and Williams (2005) that compared station temperature time series with those of neighboring stations. Stations with statistically significant change points in their temperature time series were removed from the analysis. This cut the 12,581 possible CONUS stations in GHCN-Daily down to 2606.

Unfortunately, stations in Alaska, Hawaii, Puerto Rico and the U.S. Virgin Islands are often too far apart for the neighboring stations statistical analysis of Menne and Williams (2005) to work reliably. Each station time series from these regions were individually evaluated. After first removing stations with short time series, plots of each time series were evaluated and stations that had detectable problems were removed. Then each station was subjected to a homogeneity test (specifically, the RHTest which is a homogeneity test written in the statistical language "R" for use at regional climate change workshops; Wang and Feng, 2004; Wang, 2003) which evaluated changes in station time series. While this test is good at determining changes in the characteristics of a time series and providing statistical significance to different detected changes, because the test had no comparison to neighboring stations, some of the detected changes were real changes in climate. The results of the RHTest were used as guide to additional evaluation of time series using graphs and assessment of station history information. Stations deemed inhomogeneous were removed from the analysis. The final step for Hawaii, Puerto Rico and the U.S. Virgin Islands data was to consult with the State Climatologists for those areas. Based on their advice, a few additional stations were removed from the analysis. This process of removing the most inhomogeneous stations from the analysis brought the total Alaska, Hawaii, Puerto Rico and the U.S. Virgin Islands station count down from 745 to 55.

2.3 *Mexican data*

A subset of the longest and most continuously operating 163 temperature and precipitation stations were selected from data from the Servicio Meteorológico Nacional (SMN) of Comisión Nacional del Agua (CNA). These stations cover Mexico north of 20º N and their data mainly extend over the second half of 20th century. Additional quality control and homogeneity assessments of the daily data were undertaken using the regional climate change workshop software RHTest and RClimDex (Zhang and Yang, 2004). The QC consisted of preliminary checks for identifying logical errors (e.g., Tmax < Tmin, precipitation < 0), potential wrong data defined as values exceeding a certain threshold were flagged and visual inspection of the plotted Tmax, Tmin and precipitation time series was carried out. The thresholds for defining an outlier were set to be four times the standard deviation (σ) of daily Tmax and Tmin records and six σ for daily precipitation data.

Potential errors were then validated or rejected (i.e., set to missing) by consulting (a) the original records, (b) independent sources, such as the Mexican Cold Front Index (Magaña and Vazquez, 2000) for temperature and precipitation records or the hurricane-tracks record available at National Hurricane Center for heavy precipitation events, (c) the values of adjacent days at the same station (d) data from the same date at nearby stations and (e) OLR anomalies and synoptic patterns based on Reanalysis NCEP/NCAR (Kalnay et al 1996) as well as known impacts of ENSO in precipitation (Magaña et al, 2003). Only those values that were positively found to be erroneous data were set to missing and deleted from further analysis. From the 163 temperature and precipitation records, the highest quality and most homogeneous 31 daily maximum and minimum temperature time series and 56 daily precipitation time series were selected.

3. INDICES AND ANALYSIS TECHNIQUES

The start of the set of indices used in this analysis are the 27 indices from daily data formulated and internationally coordinated by the joint World Meteorological Organization (WMO) Commission for Climatology (CCl) / World Climate Research Programme (WCRP) project on Climate Variability and Predictability (CLIVAR) / Joint WMO-Intergovernmental Oceanographic Commission of the United National Educational, Scientific and Cultural Organization (UNESCO) Technical Commission for Oceanography and Marine Meteorology (JCOMM) *Expert Team on Climate Change Detection and Indices* (ETCCDI). This suite of indices, available from http://cccma.seos.uvic.ca/ETCCDMI/, has changed since it was first used in Frich et al. (2002) and Peterson et al. (2002). Some indices have been added but more importantly the approach used to determine station level thresholds for percentile indices was improved.

The original approach calculated, for example, the 10^{th} percentile of daily Tmax by determining the value of the 10^{th} percentile of the data from a 5 day window centered on each calendar day during a base period, typically 1961-1990. This calendar day-specific value was used for that calendar day throughout the entire time series. However, it was later determined that this approach caused a slight discontinuity in the indices at the beginning and end of the base period. The solution was a bootstrap procedure described in Zhang et al. (2005a) that used that same technique for determining the appropriate threshold value for years outside the base period but for years inside the base period only used the other 29 years to calculate the appropriate threshold. This changes the threshold slightly from year to year but avoids the data for any year contributing to the calculation of the appropriate percentile threshold applied to that year's data.

Over the last several years, this suite of indices was used to examine changes in extremes in five specific areas where regional climate change workshops were held (Aguilar et al., 2005; Haylock et al., 2006; Klein Tank et al.; 2006; New et al., 2006; Vincent et al., 2005; and Zhang et al., 2005b) and one global analysis which incorporated the indices calculated at the regional workshops (Alexander et al., 2006). For this North American extremes analysis, a few additional indices were calculated in a manner consistent with formulations used by the ETCCDI and in the papers just cited.

Indices of relevant parameters were created on a station basis and then averaged together. For North American time series, anomalies of station level indices were first averaged into 2.5° latitude by 2.5° longitude grid boxes. Where a grid box didn't have any stations, the values of the indices from neighboring grid boxes were interpolated into that grid box in order to make the averaging area more spatially representative. This primarily occurred in northern areas. The grid box values were then averaged on an area-weighted basis to create North American time series. The time series figures show the annual values and a smoothed line derived from a locally weighted regression (lowess filter; Cleveland et al., 1988). An advantage of a lowess filter is that it is robust to one extreme annual value that might occur in an El Niño year, and therefore depicts the underlying long-term changes quite well.

Maps of the indices show grid box level linear trends computed using a Kendall's tau based slope estimator (Sen, 1968). This estimator is robust to the effect of outliers in the series. It has been widely used to compute trends in hydrometeorological series (e.g., Wang and Swail, 2001; Zhang et al., 2000). The significance of the trend is determined using Kendall's test because this test does not assume an underlying probability distribution of the data series. There is, however, a problem associated with the Kendall test in that the result is affected by serial correlation of the series. Specifically, a positive autocorrelation, that is likely the case for most climatological data, in the residual time series will result in more false detection of a significant trend than specified by the significance level (e.g., von Storch, 1995; Zhang and Zwiers, 2004). This would make the trends detection unreliable. Because of this, we use an iterative procedure, originally proposed by Zhang et al. (2000) and later refined by Wang and Swail (2001), to compute the trend and to test the trend significance taking account of a lag-1 autocorrelation effect. Details of the trend estimation and significance testing are explained in the work of Wang and Swail (2001, Appendix A). Throughout our paper, a trend is considered significant if it is statistically significant at the 5% level. Grid boxes where the trend is significant are highlighted.

While the analysis used data from 1950 through 2004, not all grid boxes had the same period of record. A trend for a grid box was plotted in the figures if the grid box average time series was at least 25 years long. This low threshold allows the maps to be fairly complete and show the local trends in the indices where data are available. But it also means that some grid boxes are providing trends from different periods of records and thereby enhances the appearance of spatial variability. Also, should a grid box have the same multi-decadal variability and change indicated in the North American time series, linear trends starting in 1950 may not represent the climate change over the last three decades very well.

4. RESULTS

4.1 *Different Measures of Temperature Extremes Show Similar Results*

The ETCCDI percentile indices examined changes in the 10th and 90th percentile of Tmax and Tmin. As each calendar day's threshold was determined separately, the probability of exceeding the 90th percentile is just as likely in winter as it is in summer. The detection probability of trends depends on the return period of the event and the length of the observational series. For time series with a typical length of ~50 years, the optimal return period for detection is 10-30 days (Frei and Schär, 2001; Klein Tank and Können, 2003). Conversely, detection of a trend would be exceedingly difficult with a measure of extremes that would only occur a few times in the course of 50 years. Therefore, the prime value of using a threshold of extremes that on average is exceeded every 10 days is in detection of trends. But the downside is that such values are not the extremes that have the most significant impact.

It was recommended at the July 2005 meeting on *North American Weather and Climate Extremes: Progress in Monitoring and Research* in Aspen that extremes farther out on the tail be analyzed as well. Therefore, analysis was done on the 10th, 5th and 2.5th percentiles, not only to provide insights into changes of rarer events (e.g., the 97.5th percentile would be exceeded on average only nine times a year), but to see how changes in the data points farther out on the tails of the distribution compare to changes in the 10th percentile.

Time series of North American area-averaged changes in maximum and minimum temperature extremes are shown in Figures 3-6. The figures show not only that cold extremes are decreasing and warm extremes are increasing, but also that very similar changes are indicated by 10th or 90th percentile and measures farther out on the tails of the distribution. Figure 7 shows the spatial distribution of trends in one of these measures of extremes, the days exceeding the 90th percentile in minimum temperature. Positive trends, and statistically significant positive trends, are widely distributed. However, there are some areas with negative trends, particularly northeastern Canada and western central Mexico, and a large area in the southeastern U.S. does not show a positive trend. This general pattern is fairly similar for the other extremes shown in Figures 3-6.

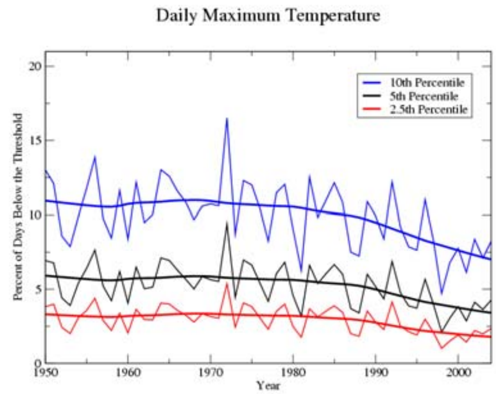

Figure 3. North American area-averaged percent of days with maximum temperature below the 10th, 5th and 2.5th percentiles. Note that all three time series have similar behavior.

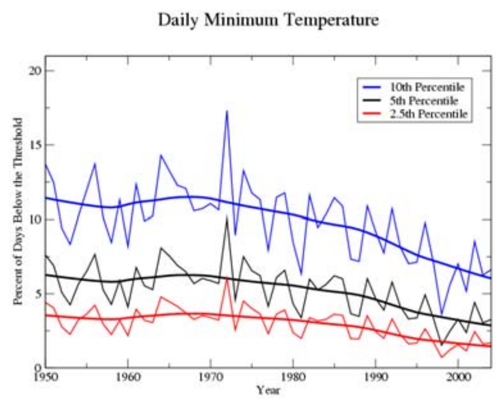

Figure 4. Same as Figure 3 except for minimum temperature.

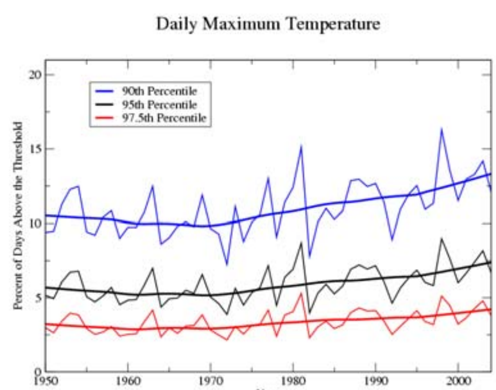

Figure 5. North American area-averaged percent of days with maximum temperature above the 90th, 95th and 97.5th percentiles.

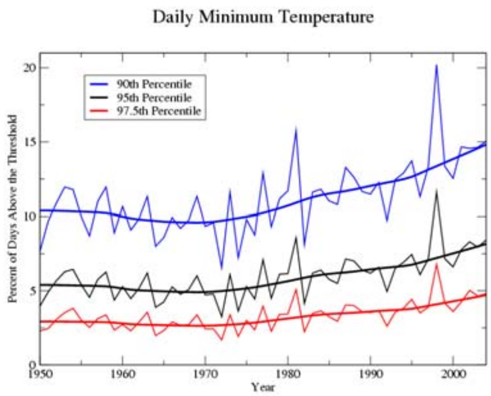

Figure 6. Same as Figure 5 but for minimum temperature.

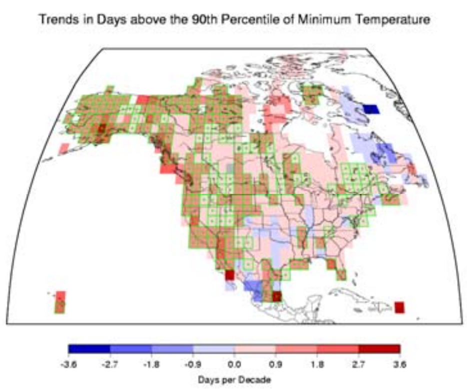

Figure 7. Grid box (2.5° latitude by 2.5° longitude) level trends of days above the 90th percentile of minimum temperature. Grid boxes with trends that are statistically significant at 5% are outlined in green and have a green circle in their centers.

Figures 3-7 reflects changes in individual days. Often several days in a row of warm or cold temperatures can cause impacts that individual extreme days can not. Therefore, the ETCCDI defined a Warm (Cold) Spell Duration Index as the annual count of days with at least 6 consecutive days when maximum (minimum) temperature is above (below) the 90th (10th) percentile. These can occur any time during the year. Examination of Figure 8 indicates that cold spells have decreased since 1950 while warm spells decreased until ~1970 and then increased. The change in these indices indicates that the observed changes in extremes are not limited to isolated days.

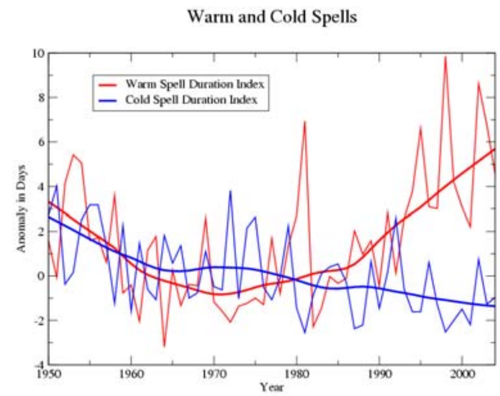

Figure 8. Warm and Cold Spell Duration indices.

4.2 *The Warmest and Coldest Extremes are Changing Differently*

The percentile indices presented in the previous section were determined throughout the calendar year. Two approaches are used to examine how the warmest and coldest days of the year are changing. The first examines the number of days exceeding the 90th percentile of maximum and minimum temperature for the hottest month of the year, July, and the number of days below the 10th percentile of maximum and minimum temperature for the coldest month of the year, January. On average during the base period, these thresholds represent the three hottest temperature readings of the hottest month of the year and the three days with the coldest temperatures of the coldest month of the year. Examination of Figure 9 indicates that, on a North American area-averaged basis, the number of cold days is decreasing with maximum and minimum temperature decreasing at about the same rate. The number of warm days is increasing, as shown in Figure 10, but minimum temperature has a greater increase than maximum temperature.

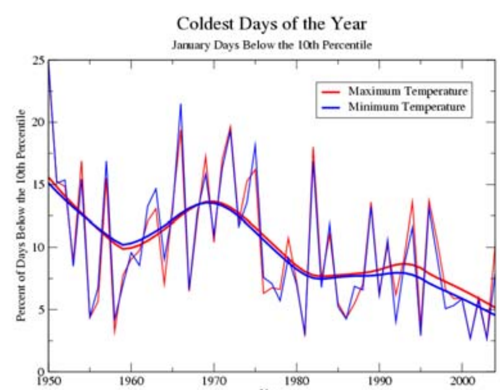

Figure 9. The percent of January days below the 10th percentile has been decreasing, with both maximum and minimum temperature showing similar changes.

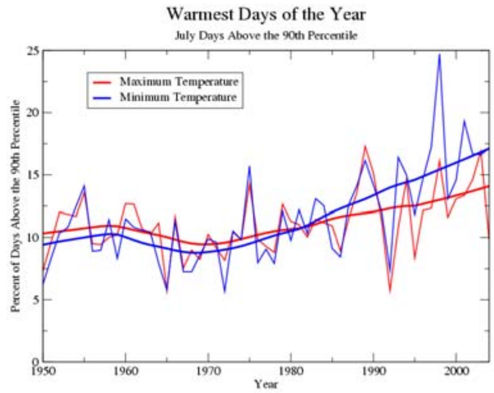

Figure 10. The number of July days above the 90^{th} percentile has been increasing, with minimum temperature showing a greater increase than maximum temperature.

The second approach looks at the annual temperature extremes. Rather than a count of the number of days exceeding a threshold, this is a measure of the actual warmest and coldest maximum and minimum temperature observed in a year. Figure 11 shows that the highest annual maximum and minimum temperature have increased ~1°C since the mid-1960s. The coldest temperatures of the year have much more variability than the hottest temperatures, as shown in Figure 12. Unlike the trends in the number of July days exceeding the 90^{th} percentile, this measure of extremes indicates that maximum and minimum temperatures are increasing at about the same rate, ~3.5°C since the late 1960s.

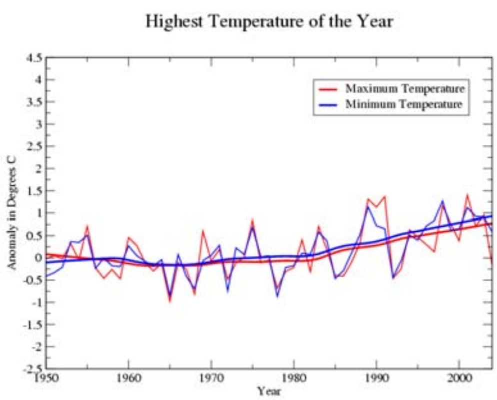

Figure 11. The highest maximum and minimum temperature observed in a year have increased ~1°C since the mid-1960s.

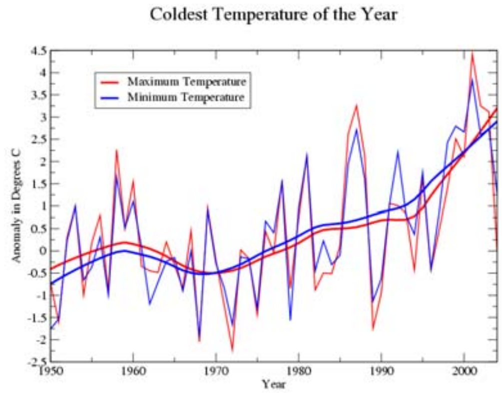

Figure 12. The coldest maximum and minimum temperature observed in a year have increased ~3.5°C since the late-1960s. As comparison with Figure 11 indicates, while this increase is larger than that experienced by the warmest temperature of the year, the variability of the coldest temperature is also larger.

4.3 *Heavy Precipitation is Increasing*

Several indices have been developed to track changes in precipitation intensity. Figure 13 shows the Simple Daily Intensity Index, which is simply the total annual precipitation divided by the number of days with precipitation equal to or greater than 1 mm. This threshold is designed to insure that changes in how an observing network treats trace precipitation does not impact the index. The increases in the Simple Daily Intensity Index revealed in Figure 13 indicate that on days when precipitation does occur, it tends to be heavier. The spatial distribution of trends in this index, shown in Figure 14, reveals that the change in intensity of precipitation is not as uniform as the changes in temperature shown earlier.

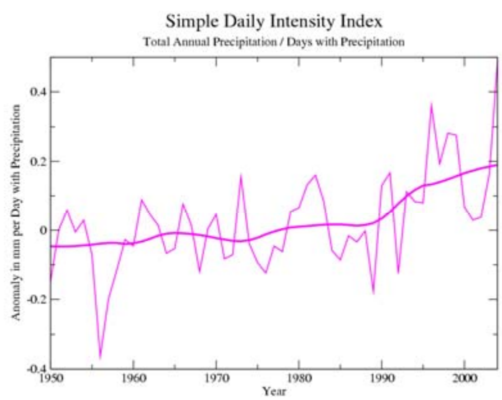

Figure 13. The Simple Daily Intensity Index has been increasing. This index is simply the total annual precipitation divided by the number of days with precipitation. So increases in this index indicate that on days when precipitation does occur, it tends to be heavier.

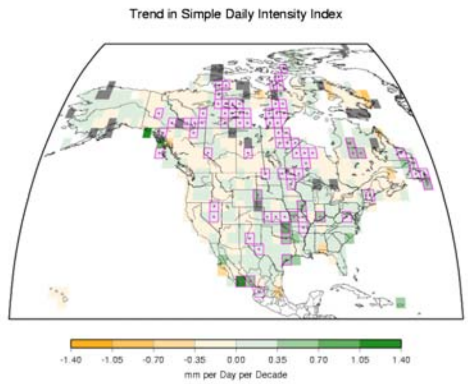

Figure 14. Grid box level trends in the Simple Daily Intensity Index. Grid boxes with trends significant at the 5% level are outlined in magenta and have a magenta circle in their centers. Grid boxes in gray have a trend of 0.00.

The annual precipitation from days exceeding the 95th and 99th percentile of daily precipitation has been increasing on a North American area-averaged basis, as shown in Figure 15. The highest one day and five day precipitation events are also increasing (see Figure 16). Grid box level trends in the maximum one day precipitation in Figure 17 show that many regions have negative trends in this index but all the statistically significant trends are positive.

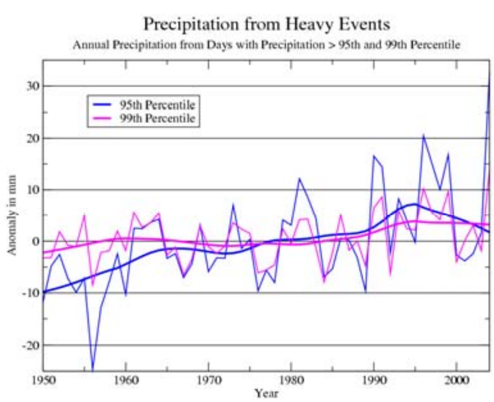

Figure 15. Annual precipitation from days with precipitation greater than the 95th and 99th percentiles of daily precipitation has been increasing.

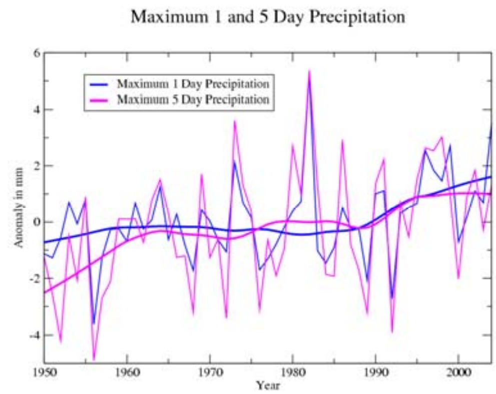

Figure 16. Maximum one day and five day precipitation has been increasing.

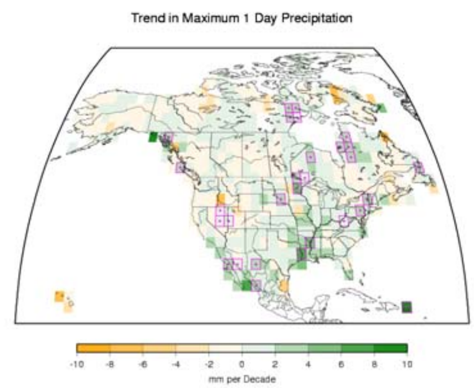

Figure 17. Grid box trends in maximum one day precipitation. Grid boxes with statistically significant trends are highlighted.

4.4 *Biologically Sensitive Indices*

Growing Season Length

The Growing Season can be defined in many different ways. Jones and Briffa (1995) calculated the start of the Growing Season for the former Soviet Union as the last day of the first five-day spell for which each daily mean temperature remained above 5°C and the end was defined as the last day of the last such spell of the year. Jones et al. (2002) modified that definition to include as the first/last five-day period had to occur after/before the last/first frost of the winter season. We are using the Growing Season definition used by the ETCCDI, which starts in the spring with the first span of at least 6 days in a row with each day having a mean temperature greater than 5°C. The Growing Season is defined to end in the autumn with the first span of 6 days in a row with each day having a mean temperature less than 5°C.

Examination of Figure 18 indicates that the start of the growing season is getting earlier and the end of the growing season is getting later. However, the changes in spring are greater than the changes in the fall, with the North American area-averaged growing season now starting ~5.5 days earlier than it did in the mid-1960s. Figure 19 shows the spatial variability of the change in growing season length. The widespread regions where the linear trend since 1950 is positive dominates the map, but there is also a noticeable region in the central and southern CONUS where the trends are negative.

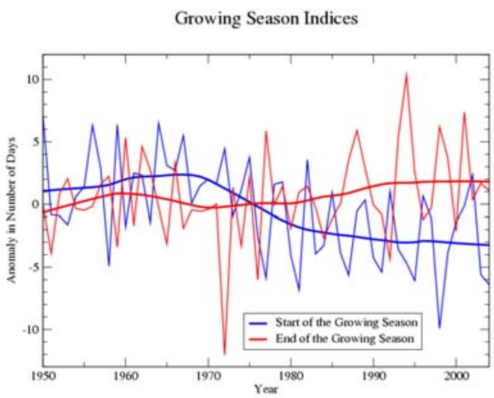

Figure 18. The Growing Season has been increasing. While start of the Growing Season is getting earlier and the end is getting later, the magnitude of the changes is greater in the spring than in the fall.

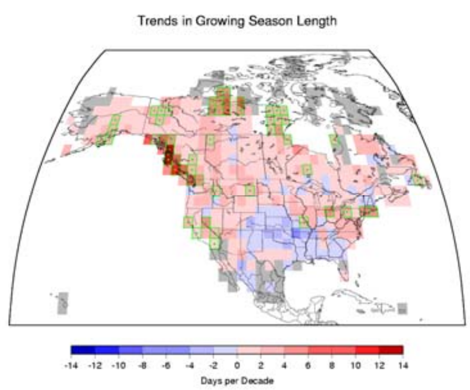

Figure 19. Grid box level trends in the length of the growing season. Grid boxes with statistically significant trends are highlighted.

False Springs

Hard freezes that occur in the spring after the growing season has started adversely impact plants and the animals that depend on the plants. These episodes are referred to as False Springs. Complicating analyses of False Springs is the fact that every plant species responds differently. For example, the False Spring for the yellow birch in eastern Canada requires daily maximum temperature to exceed 4°C after being below freezing for at least two months during winter, greater than 50 growing degree days to start the spring growth, and then the daily minimum temperature needs to drop to -4°C (Bourque et al., 2005). Yet many plants, such as corn or soybeans, die back at much warmer temperatures. A higher minimum temperature threshold of -2.2°C is often used (e.g., Schwartz et al., 2006). Indeed a minimum temperature of -2.2°C (28°F) is a commonly used threshold in the U.S. for plant freezing related indicators such as when allergy season is over in the fall. Our False Spring Index is defined as the number of days between the start of the growing season in the spring and the last -2.2°C or lower minimum temperature in the first half of the year. Should no hard freeze occur after the start of the growing season, the index value is zero.

The area-averaged false spring index would become larger if the length of time between the start of the growing season and a hard freeze increases or the number of stations indicating a False Spring increases. Both events are detrimental to plants and animals as the longer the period before a hard freeze, the greater the chance that plant dependent insects are out of dormancy and that insect dependent birds have migrated into the areas. Figure 20 shows the change in North American area-averaged False Springs. The index rose from 1950 to the mid-1960s and then decreased, though the interannual variability is quite large.

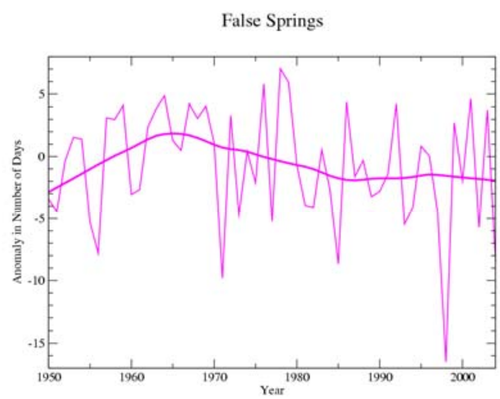

Figure 20. False Springs have been decreasing since the mid-1960s, though the interannual variability is quite large.

5. DISCUSSION

North American area-averaged maximum and minimum temperature extremes are, to a first approximation, changing the way one might expect given the changes in mean temperature (e.g., see Figure 21). There are many different ways to assess changes in extremes. Just looking farther out on the tail of the distribution, as shown in Figures 3-6 provides little extra insight into how extremes are changing. However, examining days exceeding percentile thresholds can indicate something quite different than changes in the actual temperature. For example, changes in the number of warmest and coldest days of the year, Figures 9 and 10, indicate about the same magnitude of change for the hottest summer days compared to the coldest winter days. On the other hand, the changes in the coldest and warmest temperature experienced in a year, Figures 11 and 12, indicate that cold winter extremes are warming faster than summer hot extremes. Or to put it another way, rather than warming, North America is becoming less cold.

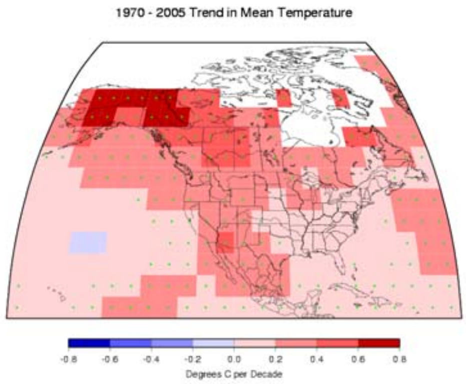

Figure 21. Trends in mean temperature for the U.S. and surrounding areas since 1970. When the trend in a 5° latitude by 5° longitude grid box is statistically significant at the 5% level, a green dot is put in the center of the box. Data from Smith et al. (2005).

These differences are easy to reconcile because the interannual variability is greater in the winter than summer. If the data from Figures 11 and 12 were normalized by dividing the temperature values by the standard deviation of the annual time series, cold winter extremes appear to have the same amount of warming as hot summer extremes, as indicated by Figures 22 and 23.

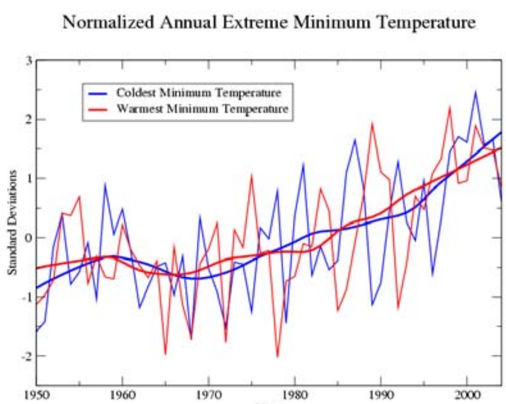

Figure 22. The annual extreme warmest and coldest minimum temperature time series shown in Figures 11 and 12 normalized by dividing by their standard deviations.

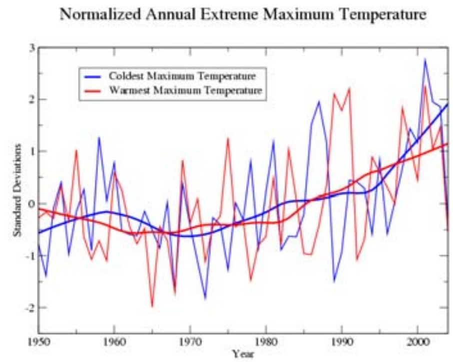

Figure 23. The same as Figure 20 except for maximum temperature.

The growing season indices are, perhaps, less measures of changes in extremes than ways to integrate changes of both means and extremes into a biologically sensitive index. The growing season was documented to be increasing with the start getting earlier and the end getting later. False Springs have been decreasing in recent decades, although the changes are small compared to the interannual variability.

The measures of precipitation extremes primarily focused on changes in heavy precipitation. Several different indices were examined and they all indicated that heavy precipitation is increasing. One non-extreme ETCCDI precipitation index, Consecutive Dry Days, was not shown because (a) it examines very different physics in different parts of North America which has seasonally dry regions and (b) very few areas show any statistically significant trends in this index. On a North American area-averaged basis, the number of Consecutive Dry Days decreases from 1950 to the mid-1980s and then increased at about the same rate as it decreased.

6. SUMMARY AND CONCLUSIONS

Detailed homogeneity assessments of daily maximum and minimum weather observing station data from Canada, the United States and Mexico enabled analysis changes in North American extremes starting in 1950. The measures of extremes assessed were primarily indices developed by the joint CCl/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices. Similar decreases in cold extremes and increases in warm extremes were found when examining the 10^{th}, 5^{th} and 2.5^{th} percentiles. Annual extreme cold temperatures are warming faster than annual extreme warm temperatures when the parameter measured is the actual temperature but cold and warm extremes are changing about the same when examined on a percentile or normalized basis. By any of several measures, heavy precipitation has been increasing in recent decades and the average amount of precipitation falling on days with precipitation has also been increasing. These changes in extremes are likely to impact natural ecosystems as well as agricultural and societal infrastructure.

7. ACKNOWLEDGEMENTS

The authors wish to thank Pao-Shin Chu and Cheri Laughran from the office of the Hawaiian State Climatologist and Robin Williams of the Office of the Puerto Rico State Climatologist for their advice regarding the reliability of data from specific stations in their areas. The staff of the Servicio Meteorológico Nacional (SMN) of Comisión Nacional del Agua (CNA) is greatly appreciated for the provision of Mexican data.

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