Exhibit No: ___
Issues: Weather Normals
Weather Normalization
Witness: Robert E. Livezey
Exhibit Type: Direct
Sponsoring Party: Missouri Gas Energy
Case No: GR-2009-___
Date: April 2, 2009

MISSOURI PUBLIC SERVICE COMMISSION

MISSOURI GAS ENERGY

CASE NO. GR-2009-__

DIRECT TESTIMONY OF

DR. ROBERT E. LIVEZEY

Jefferson City, Missouri

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QUALIFICATIONS

Q. PLEASE STATE YOUR NAME AND BUSINESS ADDRESS.

A. Dr. Robert Livezey, 5112 Lawton Drive, Bethesda, MD 20816.

Q. WHAT IS YOUR OCCUPATION?

A. Since retiring as Chief of National Weather Service ("NWS") Climate Services in 2008, I have been a self-employed consultant on matters related to climate normals, variability, change, and prediction.

Q. PLEASE DESCRIBE YOUR QUALIFICATIONS TO TESTIFY IN THIS CASE.

A. My doctoral research at the Pennsylvania State University, completed in 1973, addressed the energy balances and controls of planetary-wide wind and storm systems that regulate the globe's climate. For 33 of the intervening 36 years, my work and research has been focused on the fields of climate variability, change, and prediction.

I am considered one of the top experts in the world on climate statistics[1] and estimating and tracking weather/climate normals and post-war climate change over North America, and as possibly the leading expert worldwide on short-term North American climate variations and their prediction. I have produced almost 60 peer-refereed publications and book chapters and at least that many conference pre-prints, post-prints, and the like. Almost all of these publications are directly relevant to topics I discuss in this testimony. Awards and appointments from academia, the National Oceanographic and Atmospheric Administration ("NOAA"), and professional associations have institutionally recognized my expertise. I was awarded a Commerce Department Gold Medal in 1998 and elected as a Fellow of the American Meteorological Society ("AMS") in 1993. Earlier, I received an AMS Editor's Award and served as Editor of the prestigious AMS *Journal of Climate* ("JOC"), where I was responsible for all submissions on climate statistics and prediction. I have been a member of the AMS Committee on Climate Variability and twice the chair of the Committee on Probability and Statistics, and very recently became a member of the AMS Publication Commission.

Q. **WHAT IS YOUR PROFESSIONAL EXPERIENCE?**

A. From 1973 to 1976 I held two faculty positions (at Penn State and the University of Missouri-Columbia) followed by three years as a hurricane modeler in Washington. From 1980-84 I served as a journeyman climate forecaster and solidified my climate research credentials at NOAA's Climate Prediction Center ("CPC", f/k/a as the Climate Analysis

[1] I am listed in the acknowledgments or table of contents of the three primary text sources for this subject. Recently, I have been invited to be a lecturer for the prestigious 6th GKSS School of Environmental Research, the School on Statistical Analysis in Climate Research, to be held in Lecce, Italy, in October of this year (see http://coast.gkss.de/events/6thschool/syllabus.html).

Center at that time) before moving on to NASA's Goddard Space Flight Center as Chief of the Experimental Climate Forecast Center. After two years (in 1986), I returned to CPC, where I served as both Senior and Principal Scientist and was Lead Seasonal Forecaster during my tenure through 1999. In my last eight years of federal service (2000-2007), I served as Chief of NWS Climate Services, and was cited for this service through five awards, including two prestigious NOAA Administrator Awards. As head of all NWS Climate Services, I was responsible for policy, customer requirements, and management of the infrastructure for NWS climate observations, forecasts, and information. This required close external working partnerships with NOAA's National Climatic Data Center ("NCDC"), which is the organization responsible for managing climate data and producing official climate normals, with the university-based Regional Climate Centers, and with the American Association of State Climatologists. The latter organization has elected me to Associate Membership and invited me to serve *ex officio* on its Executive Committee.

Q. HAVE YOU PREVIOUSLY PROVIDED EXPERT WITNESS TESTIMONY?

A. Yes, I have. Since retirement from federal service, I have filed expert witness testimony before both the Iowa Utilities Board and the Colorado Public Utilities Commission.

INTRODUCTION

Q. FOR WHOM ARE YOU TESTIFYING IN THIS MATTER?

A. I am testifying on behalf of Missouri Gas Energy ("MGE" or "Company").

Q. WHAT IS THE PURPOSE OF YOUR PREPARED DIRECT TESTIMONY?

A. My testimony will provide an explanation of climate normals, review my team's research and conclusions regarding changing climate normals, compare various methods for predicting the current climate, and make a recommendation to the Missouri Public Services Commission ("PSC") for defining "normal" weather for purposes of ratemaking.

Q. HOW DO YOU ORGANIZE THE BALANCE OF YOUR DIRECT TESTIMONY?

A. My testimony is organized into the following sections:

- CLIMATE NORMALS, THEIR USE AND ESTIMATION
- RESEARCH ON TRACKING CLIMATE AND ESTIMATING NORMALS
- IMPLICATIONS FOR MISSOURI NORMALS
- OVERVIEW AND RECOMMENDATIONS

Q. DO YOU SPONSOR ANY SCHEDULES?

A. Yes, I do. I sponsor the following Schedules:

- Schedule REL-1 – "Estimation and Extrapolation of Climate Normals and Climatic Trends" coauthored by myself and published in the November 2007 issue of the *Journal of Applied Meteorology & Climatology,*
- Schedule REL-2 -- April 23, 2008, *USAToday* article regarding increasing opposition to the U. S. Department of Agriculture's intention to base its latest release of its official "Plant Hardiness Zones" map on 30-year average temperatures, and

- Schedule REL-3 – "Redefining 'normal'" by Bob Henson in *UCAR Winter 08-09 Quarterly.*

CLIMATE NORMALS, THEIR USE AND ESTIMATION

Q. PLEASE EXPLAIN HOW YOUR EXPERIENCE LED YOU TO YOUR RESEARCH ON CLIMATE NORMALS.

A. All three of the major roles I have played in climate science (researcher, forecaster, and services manager) intersect at climate normals. Analyses of climate variability have climate normals as their frame of reference; climate forecasts are issued in terms of departures from "normal;" and official climate normals and the observations underlying them are a major joint responsibility of NCDC and NWS. Thus, early in my career I had to confront directly the problem of estimating normals from data. By the late 1990s, I came to realize that I would have to account explicitly for climate change in the estimation of weather normals. More specifically, I discovered during my tenure at CPC that cold-season United States temperatures had been increasing over most of the country over the last few decades at a surprising rate, and concluded that CPC would have to find a new way to account for these changes in its seasonal forecasts.

Q. PLEASE DISCUSS IN SIMPLE TERMS CLIMATE NORMALS AND THEIR ESTIMATION

A. Changes in weather from year to year can be and often are very large. Because we cannot forecast these year-to-year weather changes, we have to rely on what we would expect average conditions over a number of years to be. This average is what we typically refer to as "climate normals."

If there were no such thing as climate change, then it would be easy to estimate a climate normal if we had a good data record: the climate normal would be just the average over a large number of past years (the World Meteorological Organization "WMO" convention is 30 years). The result of this averaging for heating degree days ("HDDs") would be a good "middle-of-the-road" basis for setting utility rates; on the average, it would be expected to be far closer to what actually occurs than would, say, a 10-year or 5-year average. This is because it is more difficult to smooth out, confidently, the large year-to-year changes when there are fewer and fewer years in the average. As the averaging period gets smaller and smaller, our confidence becomes less and less that the average is near the "middle of the road," the climate normal. When the period decreases to a single year, the "standard error," which is the average error you would expect when using the normal to represent any other year, will be the greatest of all, and thus our confidence in the estimate is at its least.

If the climate is changing, then determining what is "normal" becomes more difficult; the slow change has to be sifted out and distinguished from the large, almost (but not totally) random year-to-year fluctuations. Because weather changes from year to year are so large and not entirely random, in short segments of data, this "climate noise" sometimes gives the appearance that a climate change is occurring when it is not. In order to distinguish real climate change from this "climate noise," which is necessary for us to know where the climate is today, we have to be guided by the body of knowledge, both empirical and theoretical, that meteorological and climatological science can provide. This was the basis for my work at NWS on normals described in the next section.

Q. WHY DOES NOAA CALCULATE AND REPORT NORMALS?

A. The main reason for calculating normals is to obtain representative descriptions of expected meteorological conditions at specific locations and times of the year, i.e. climate conditions, which are used for planning purposes and benchmarks for actual conditions (e.g. referring to conditions as "above" or "below" normal). In the context of "expected" conditions, normals have been used as base-line forecasts, or as best guesses of what future conditions (surface air temperatures, sea temperatures, precipitation, etc.) will be beyond the accuracy range of daily weather forecasts (5 to 10 days depending on time of year) and monthly and seasonal forecasts (out to a year).

Q. PLEASE DESCRIBE RELEVANT "PARTS" OF NOAA FOR NORMALS AND SOME HISTORY BEHIND 30-YEAR NORMALS.

A. Three parts of NOAA play the dominant roles in climate services and science, but only two of them play direct roles in the production of official normals. The two are NWS, which is responsible for the observations that are used to compute official normals, and (as previously noted) the National Environmental Satellite and Information Service's ("NESDIS") NCDC, which is responsible for normals production and dissemination. Climate prediction (forecasts beyond the range of accurate daily weather prediction) is also the responsibility of NWS and is conducted at CPC for seasonal forecasts out to a year in advance. Oceanic and Atmospheric Research ("OAR") is the third part of NOAA with a large role in climate. OAR produces multi-decadal climate projections.

Climate normal practices have evolved over many years but only became somewhat standard after the WMO recommended in 1984 the use of "climatological standard normals" consisting of 30-year averages updated at least every 30 years (1931-1960, 1961-1990, etc.). WMO also recommended updated 30-year "normals" every decade, a practice adopted by many countries including the United States. Thus, new official normals based on 1971-2000 data were released in 2003 by NCDC to replace those based on 1961-1990, and an updated set will be available in the early 2010s.

As it turns out, NOAA does not use normals at all in its routine daily weather forecasts out to 7 days. But more significantly, 30-year normals are not used at all in their "expected conditions" context for NOAA's suite of forecasts that go beyond 7 days, i.e. for all of the climate forecasts made by CPC and OAR. Weather and climate scientists have known for decades that 30-year normals are not generally of value for either day-to-day weather prediction or future climate prediction. I will discuss this point more later, but for now I would note that there is a growing recognition of this among industries and some are pursuing alternatives.

RESEARCH ON TRACKING CLIMATE CHANGE AND ESTIMATING NORMALS

Q. DID YOU PERFORM ANY ANALYSES REGARDING THE PREDICTION OF NORMAL TEMPERATURES, OR CLIMATE NORMALS?

A. Yes.

Q. PLEASE EXPLAIN.

A. Most recently, I co-authored a paper entitled, "Estimation and Extrapolation of Climate Normals and Climatic Trends" that was published in the November 2007 issue of the Journal of Applied Meteorology & Climatology. I have included a copy as Schedule REL-1. At the outset, I was guided in this work by other research I had completed in the mid-1990s. This earlier research (documented in the Livezey and Smith, 1999, citations in the recent paper and described later) provided a considerable basis for attributing U.S changes to global climate change and led to a superior new methodology for estimating normals during periods of climate change.

Q. BASED ON YOUR EXPERIENCE, DO YOU KNOW OF ANY OTHER SCIENTISTS WORLDWIDE THAT HAVE STUDIED THE PREDICTIVE VALUE OF 30-YEAR WEATHER NORMALS?

A. Yes, the key papers addressing the problem since the 1950s are cited in my attached paper (Schedule REL-1). All of these are handicapped by statistical sample problems, and none are as comprehensive as my paper in their treatment of the several superior alternatives to traditional 30 year averages for a more accurate prediction of normal temperatures. Nevertheless, they all agree with my conclusion that better alternatives often do exist.

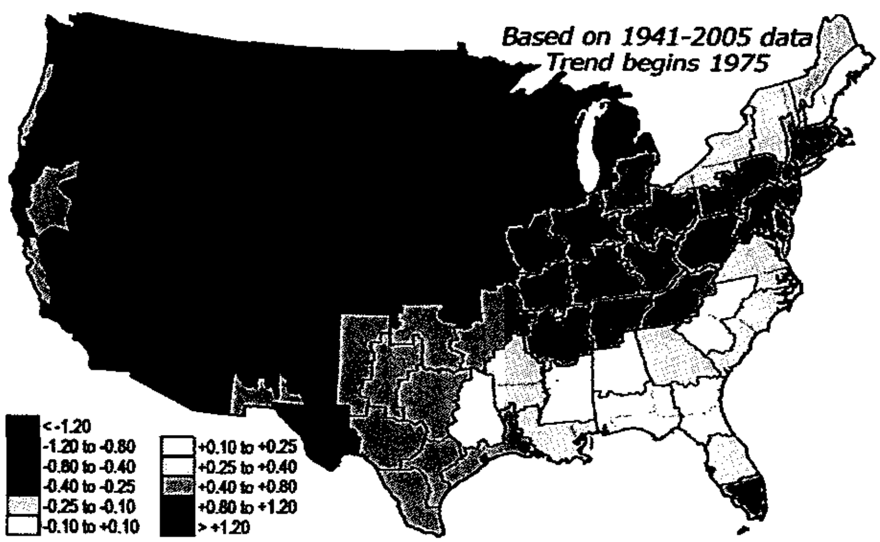
Q. IS A 30-YEAR AVERAGE STILL A REASONABLE ESTIMATE OF NORMAL TEMPERATURES?

A. No, it is not. We know that a 30-year normal will provide a relatively stable estimate when temperatures are very static, but under conditions of a warming climate, with certainty, will produce a best guess that will be cold-biased. Unfortunately, the assumption of inconsequential climate change cannot be made anymore. While there may be controversy over the cause of climate change or the seriousness of its impacts, there is virtually no reasonable controversy remaining over the fact that measurable climate change has taken place since the 1970s, globally as well as over the United States, and that the temperature increase is greatest over Northern Hemisphere continents in the wintertime. This condition is illustrated later in my testimony with some graphs of the United States.

Where it is undeniable that we have experienced decades of warming temperatures, use of a 30-year average to predict temperatures today will often result in "normal" temperatures that are significantly colder than the temperatures that will probably occur. Many individuals, businesses and organizations without knowledge of my research still mistakenly presume that the WMO 30-year standard remains a viable approach, but there is a growing intuitive awareness that new approaches are more appropriate. For example, this awareness is evidenced in an article that appeared on April 23, 2008, in *USAToday* that describes increasing opposition to the U. S. Department of Agriculture's intention to base its latest release of its official "Plant Hardiness Zones" map on 30-year average temperatures. I have included a copy of this article as Schedule REL-2.

Q. **PLEASE DESCRIBE THE CONCLUSIONS YOU DREW FROM YOUR RESEARCH.**

A. These conclusions are set forth in the 2007 paper attached as Schedule REL-1. The paper concludes that for much of the wintertime United States, 30-year normals are a very poor choice as "best guesses" for mean temperature in a given year (absent advance knowledge, which we rarely have far in advance, of the climate noise). The underlying reason for this conclusion is illustrated in the map below that shows my estimates of how much (in degrees Celsius) January through March temperatures have warmed over the United States from 1975 to 2005. The warm shades (yellow to reds) represent consequential to extremely large warming, respectively; the country figuratively has "turned red" in the map, indicating substantially warmer temperatures.



Q. ARE BETTER "BEST GUESS" CHOICES AVAILABLE?

Guided by my own earlier work and the vast, pooled work of the Intergovernmental Panel on Climate Change[2] ("IPCC") compiled in its report (Solomon *et al.*, Eds., 2007: *Climate Change, 2007: The Physical Science Basis.* Cambridge University Press), my colleagues and I have analyzed the relative performance of several alternatives for tracking changing normals; i.e., alternative best guesses for the coming winter's temperatures. Of these, we recommend one or another of two, the so-called "optimum climate normal" ("OCN") and "hinge fit," where the best method at a location depends on the easily estimated statistical character of both the climate change and climate noise. We find that the expected performance of these alternatives is generally superior to the use of 30-year normals. A conclusion from my research is that this finding is true for Missouri in particular.

Q. HOW HAS THE SCIENTIFIC COMMUNITY AND WEATHER INDUSTRY REACTED TO YOUR RESEARCH AND 2007 PAPER?

A. So far, the conclusions in the 2007 paper have not been challenged, either formally or informally, and have been favorably received by two governmental agencies, the CPC and the NCDC. For prediction purposes, the CPC has used and will continue to use variations of the alternatives (OCN or hinge fit) to the 30-year average recommended in my 2007 paper. Recall my point earlier that 30-year normals were originally intended to serve two purposes, as estimates of expected conditions (i.e. a forecast role) and as

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[2] The IPCC is a scientific intergovernmental body set up by the WMO and by the United Nations Environment Programme (UNEP). It is open to all member countries of WMO and UNEP. U.S. participation includes every Department and Agency concerned with or impacted by changing environmental conditions.

benchmarks for current or actual conditions (i.e. a reference role). "Official" CPC forecasts no longer rely on 30-year normals as a forecast tool. While not used to forecast, the CPC does continue their use as references (in the form of "below normal," "above normal," etc.) as a convenience for the public. In other words, the "official" 30-year normals are used now only in packaging CPC forecasts, not in making them.

The other agency favorably reacting to my paper, NCDC, has initiated work that will lead to the release soon of both alternative statistics recommended in my 2007 paper to provide users the opportunity to consider their use.[3] Thus, my work is being taken seriously by official agencies that produce and rely on normals, and has not been challenged to date.

Q. WHAT HAVE BEEN THE REACTIONS TO YOUR RESEARCH AND CONCLUSIONS BY THE OFFICIAL AGENCIES YOU HAVE MENTIONED?

A. Official NOAA climate forecasters (CPC) had previously decided not to use 30-year averages at all to arrive at their best guess for future seasons and my work gave them additional support for their position and new alternatives to consider. Likewise, NOAA's official climatologists (NCDC) have fully acknowledged the need to augment, if not totally replace, 30-year normals in response to my advice. I should also point out that my research was conducted in my capacity as a government official, and the 2007 paper was published with the approval of NOAA.

[3] NCDC's progress and release plans are described in an article by Bob Henson in the *UCAR Winter 08-09 Quarterly* included as Schedule REL-3.

Q. PLEASE GENERALLY DESCRIBE THE RESEARCH THAT LED TO THE CONCLUSIONS OF THE 2007 PAPER.

A. In the mid-1990s, I performed research directed at trying to relate winter-to-winter changes over the United States to global climate observations. Even though I was not searching for a climate change signal and was not explicitly computing trends, I found that when the effects of climate noise (*e.g.*, El Nino/La Nina and the North Atlantic Oscillation)[4] are removed, there is a relationship between a global-scale pattern in ocean temperatures and U. S. winter temperature patterns. This relationship showed little or no change in average temperatures from one decade to the next for the U.S. and large key areas over the global ocean from about 1940 to around the mid-1970s, and relatively steady warming thereafter for both. If this relationship was shown graphically, the viewer would note a 30-plus-year period of stable temperatures until about 1975, with a clear upward trend thereafter, with a pivot point around the year 1975. It resembles a hinge, which is why we used the term "hinge fit" in the 2007 paper. I found that this "hinge" shape accurately described the graphical representation of the post-1940 behavior of the global mean annual temperature also, as I will illustrate below. I also noted from other researcher's papers that the global ocean temperature pattern associated with global climate change was the same as the pattern I found associated with the U. S. wintertime changes. Thus, my completely independent analysis ties the climate change patterns in the oceans and in the global average temperatures over the last 60 years to changes observed in U. S. temperatures. I did my work with an entirely different methodology

[4] El Nino/La Nina and the North Atlantic Oscillation are major year-to-year swings in central equatorial Pacific ocean temperatures and North Atlantic wind and pressure systems respectively that have a substantial impact on U.S. winters.

from other existing global change studies, lending additional confidence to the conclusions.

Q. WHAT WAS THE NEXT STEP IN YOUR WORK?

A. My next step was to see whether I could repeat my results (discovering that the "hinge" shape describes the winter warming pattern and its post-1940 changes) by making changes in the input data to my analysis; *i.e.* to see whether the results were robust. The essence of the United States pattern and its evolution in time were unchanged when I included data prior to 1940, and for a broader range of locations, including Canada, Alaska, as well as the lower 48 states.

Q. WHAT CONCLUSION DID YOU DRAW FROM THESE MID-1990S ANALYSES?

A. My conclusion in 1998 was that climate change over the United States is substantially tracking global climate change.

Q. DO OTHER SCIENTISTS OR ORGANIZATIONS AGREE WITH YOUR CONCLUSION?

A. Yes. A large number of independent studies undertaken since 1998 have reached the same conclusion. These are summarized in the IPCC report (Solomon *et al.*, 2008) referenced earlier, often referred to as Working Group 1's Fourth Assessment Report ("WG1/AR4"). Figures SPM.4 and 3, shown below, are taken from the IPCC WG1/AR4's Summary for Policy Makers. In Figure SPM.4, the hinge-shaped increase in temperatures can be seen globally, for annual mean land and sea temperatures, and for all the sub-regions depicted: The graphs for each continent show little change in annual mean temperature from around 1940 until sometime in the 1970s, then increases thereafter. The seemingly large decline from 1940 to 1970 over North America is an artifact of the use of 10-year averages in the graph and a few years of extraordinarily cold conditions in the 1970s and should not be interpreted as a cooling climate.

Figure SPM.3 corroborates the fact that the globe has warmed over the last several decades by depicting consistent changes in sea level and global snow pack melting. Another feature of the temperature trends shown in the graphs is an increase in temperatures from about 1910 to 1940. All three tendencies – increasing temperatures until about 1940, then level temperatures into the 1970s, followed by a return to increasing temperatures right through to the present – are apparent in the United States graphs I will show next.

Global and Continental Temperature Change

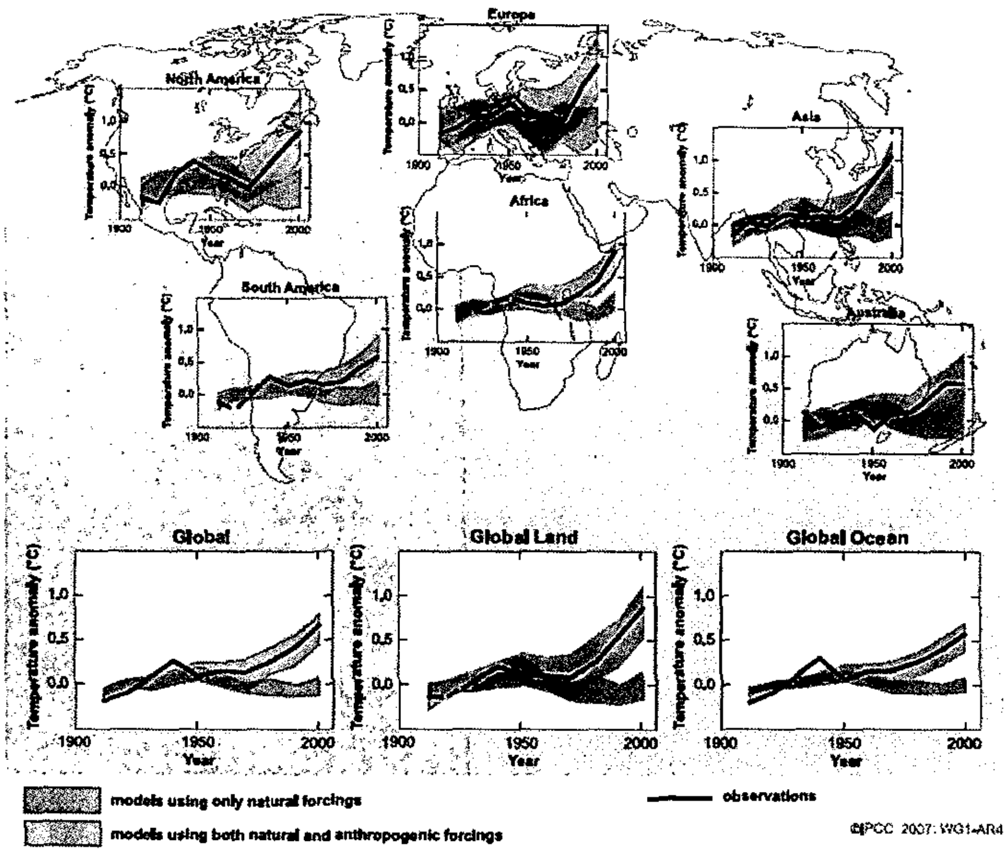


Figure SPM.4. *Comparison of observed continental- and global-scale changes in surface temperature with results simulated by climate models using natural and anthropogenic forcings. Decadal averages of observations are shown for the period 1906 to 2005 (black line) plotted against the centre of the decade and relative to the corresponding average for 1901–1950. Lines are dashed where spatial coverage is less than 50%. Blue shaded bands show the 5–95% range for 19 simulations from five climate models using only the natural forcings due to solar activity and volcanoes. Red shaded bands show the 5–95% range for 58 simulations from 14 climate models using both natural and anthropogenic forcings. {FAQ 9.2, Figure 1}*

CHANGES IN TEMPERATURE, SEA LEVEL AND NORTHERN HEMISPHERE SNOW COVER

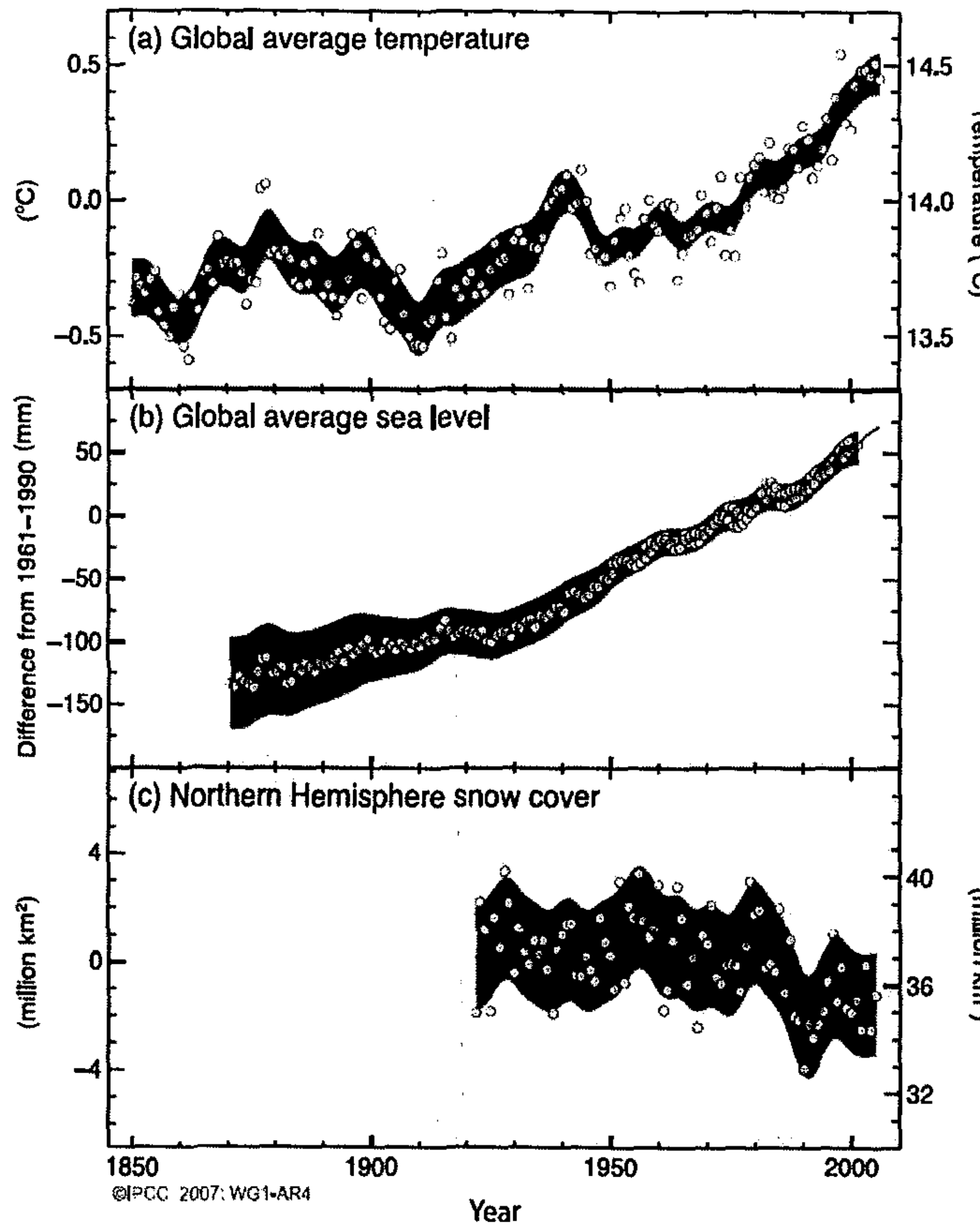


Figure SPM.3. *Observed changes in (a) global average surface temperature, (b) global average sea level from tide gauge (blue) and satellite (red) data and (c) Northern Hemisphere snow cover for March-April. All changes are relative to corresponding averages for the period 1961–1990. Smoothed curves represent decadal average values while circles show yearly values. The shaded areas are the uncertainty intervals estimated from a comprehensive analysis of known uncertainties (a and b) and from the time series (c). {FAQ 3.1, Figure 1, Figure 4.2, Figure 5.13}*

Q. DO YOU HAVE AN OPINION ON WHETHER THE TEMPERATURES IN THE UNITED STATES REFLECT THE HINGE FIT AND WARMING TEMPERATURES SINCE THE MID-1970s?

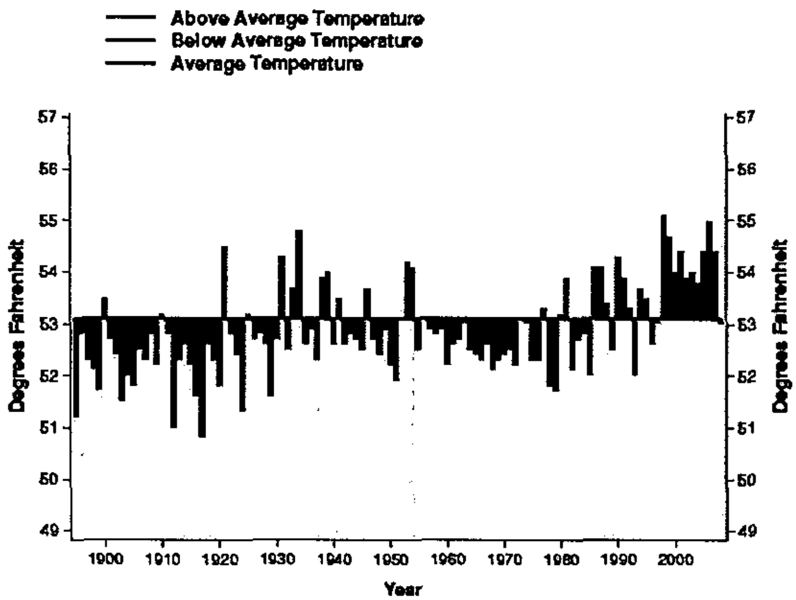
A. Yes. Generally, the temperatures in the United States (including Missouri) reflect the "hinge fit" pattern. Because Figs. SPM.4 and 3 are for larger areas than our focus here, and because those charts show annual mean temperatures, I have plotted the following three figures to show the average annual temperatures for the United States and the average winter period temperatures for the United States and Missouri. The plots show average temperatures, rather than HDDs derived from them, to follow usual NOAA practice to not emphasize just one application area.[5]

With the exception of the anomalous, unprecedented (in over 110 years), brief cold period experienced in the latter part of the 1970s, these temperature histories clearly reflect the same "warm-no change-warm" (double-hinge shape) trends previously shown for each continent in the global analysis. Temperature histories become "noisier" (show more variability) as the analysis focuses on smaller geographic areas, so to aid visualization for the Missouri winter history, I overlaid schematically the double-hinge shape reflected in the global analyses in Fig. SPM. 4. Two things should be noted about the Missouri winter temperature history. First, the trend to warmer temperatures in recent decades is not as obvious as in the other maps shown. In addition to being a smaller area, Missouri is in the zone of transition for the United States between modest temperature trends to the southeast and very large trends to the northwest (see the map on p. 14 of this

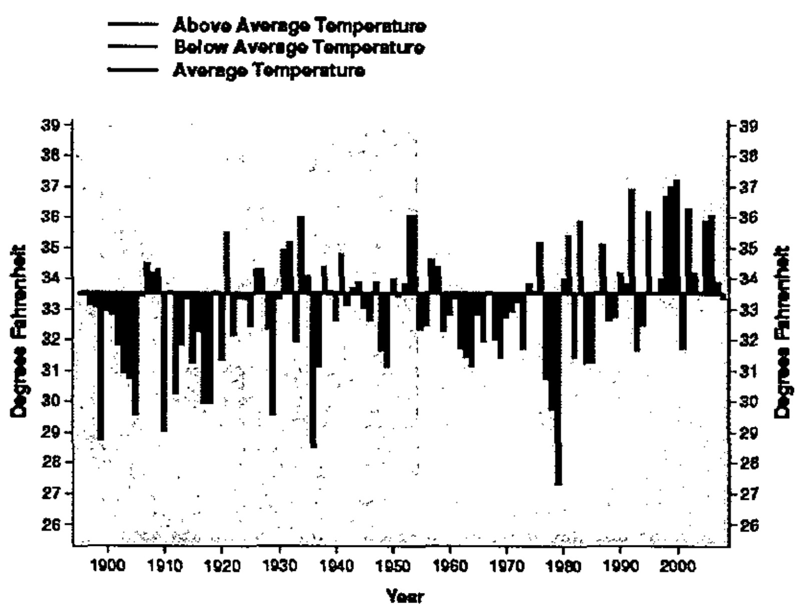
[5] The reference lines on the three graphs are the average temperatures respectively for 1971-2000.

testimony). Second, Missouri temperature records in other seasons (see Schedule REL-1, Fig. A1) indicate no trends whatsoever, underlying the significance of the winter trends.

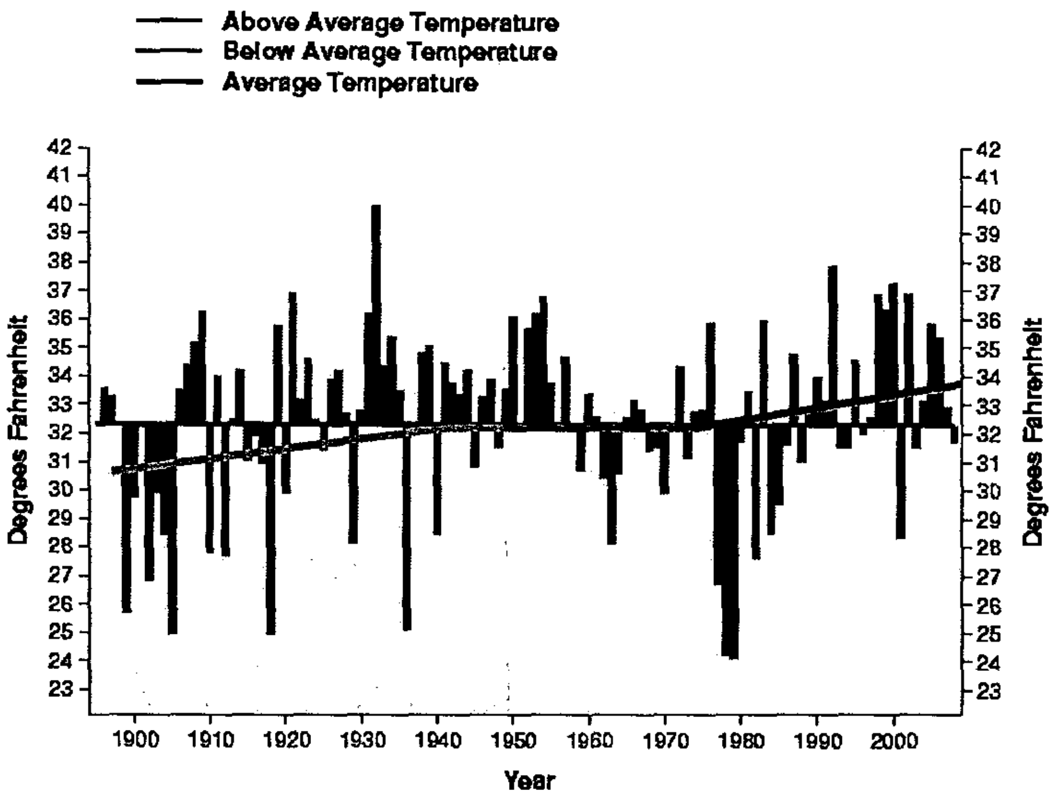
U.S. Annual Mean Temperature History



U. S. Winter Temperature History



Missouri Winter Temperature History



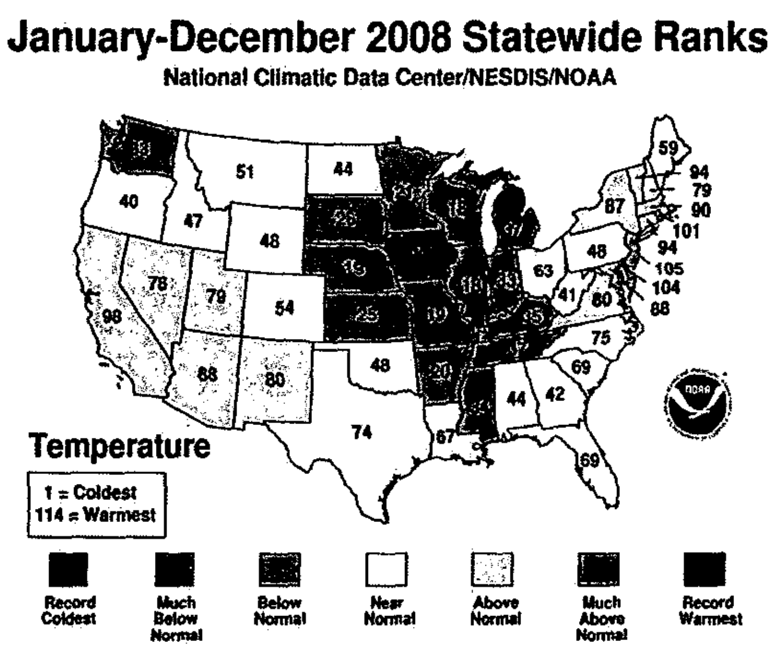
Q. 2008 WAS THE COLDEST YEAR IN A DECADE FOR THE UNITED STATES.. DOES THIS SIGNAL A SHIFT TO A PERIOD OF COLDER TEMPERATURES?

A. No. NOAA scientists have reached the preliminary conclusion that the cold U. S. temperatures for 2008 were a result of climate noise:

> What then caused the 2008 U.S. coolness? Although colder than many recent years experienced for the U.S., it was well within the range of variability associated with[in] natural internal climate fluctuations. The year of coolness does not cast doubt on the reality of global warming, but it does serve to remind that on regional and annual scales, the GHG [greenhouse gases] signal of temperature

change is still modest in amplitude compared to the intensity of natural variability.[6]

Winter, the season with the greatest warming over the last few decades for the United States and the only season with consequential warming for Missouri, was less unusual for 2008, *i.e.* the coldest in the last 7 years for the United States and last 5 years for Missouri. Globally, the relative cooling in 2008 hardly registered at all; the year was the seventh warmest year on record according to NOAA. The United States was the only land mass worldwide that exhibited a substantial area that was relatively cool, reinforcing the conclusion that it was the result of a random climate fluctuation. The map below shows state-by-state ranks of annual average temperatures (coldest in 114 years is denoted "1"; e.g. Missouri had its 19th coldest year); from a global perspective, the cold area is quite small, but Missouri was close to its epicenter in Iowa.



[6] Preliminary NOAA CSI Report, Dr. Martin Hoerling, ESRL/OAR/NOAA, lead.

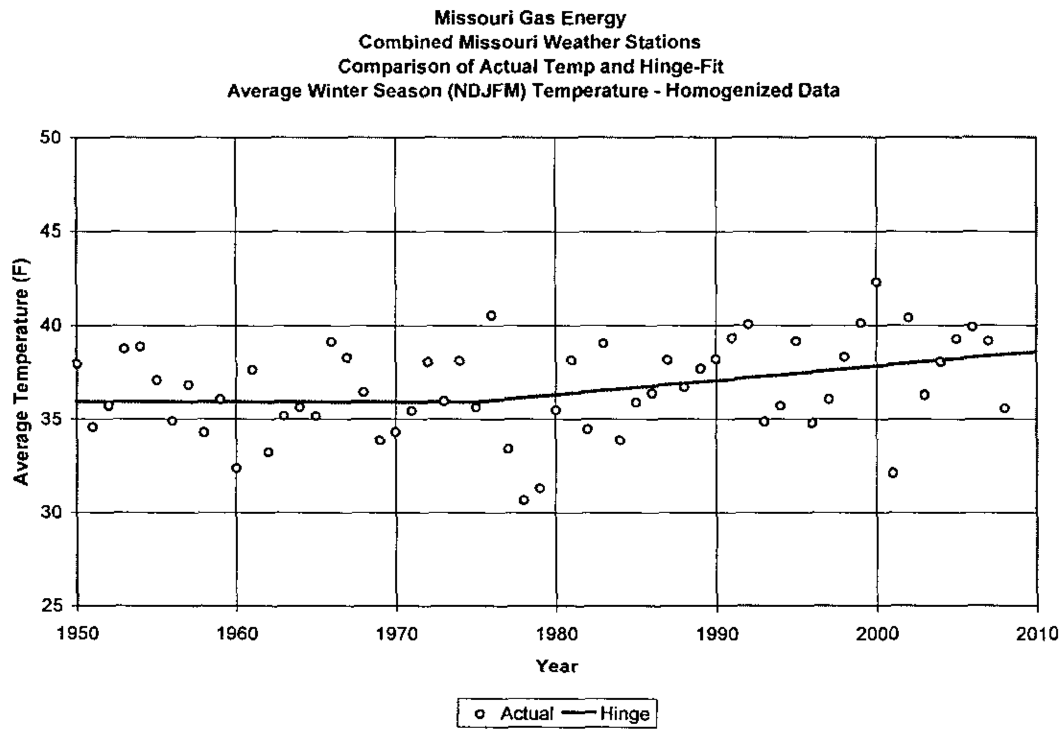
IMPLICATIONS FOR MISSOURI NORMALS

Q. WHAT CONCLUSIONS CAN BE DRAWN FROM THE UNITED STATES AND MISSOURI DATA?

A. The U.S. and Missouri winter data clearly fit the hinge shape that our research validated as a tool for tracking global climate change. Therefore, the hinge fit methodology should be much more accurate than 30-year normals in these cases. A major benefit of using pre-1975 data is that it enormously increases the confidence, in both ordinary and statistical meanings, in post-1975 temperature trend estimates. This can be seen in the Missouri winter history, illustrated above, where the two coldest years in the record occurred in the late 1970s, which should be considered a statistical aberration. A trend estimate based on data from the late 1970s to the present would dramatically overestimate the rate of winter warming in Missouri because of those two winters. Fitting a hinge averages the impact of these anomalous winters by anchoring the beginning of the trend to the average conditions over the 1940 to mid-1970s period.

The statistical technique for calculating the 2008 (or 2009) expected temperatures in Missouri would be to find the least-squares fit to the hinge shape for post-1940 data, where the fit will be especially good. An example of the calculation with post-1948, November through March ("NDJFM") data for eight stations[7] in western Missouri (representing MGE's service area) by MGE witness Larry Loos is shown below. The hinge shape represents the data well:

[7] The station temperature records used in the figure were obtained from NWS (who used them to make official local seasonal forecasts) but were produced by NCDC. The records are the same used by Mr. Loos to produce the "Homogenized HDDs" cited in his testimony and later in this testimony.



Q. WHY DO YOU USE "HOMOGENIZED" DATA IN THIS GRAPH AND LATER IN YOUR TESTIMONY INSTEAD OF THE ORIGINAL DATA AT THE EIGHT WESTERN MISSOURI LOCATIONS REPRESENTING MGE'S SERVICE AREA?

A. All historical temperature records have problems associated with them, including a variety of errors, missing data, and inconsistencies in their sites, instruments and observing practices. The records available for MGE's western Missouri service area turn out to be especially problematic, particularly with respect to inconsistencies over time.

Most of these sites have such pronounced inconsistencies that they seriously compromise the utility of the records for tracking the stations' climates, our objective here:

> Ideally, for the purposes of climate research, the period of record for U.S. in situ observations would be free of changes and inconsistencies in observational practices (e.g., station relocations, instrumentation changes, differing daily observation schedules). When present, these inconsistencies can lead to a nonclimatic bias in one period of a station's climate record relative to another, or in observations from one station relative to another. In such cases the data record is considered to be heterogeneous or "inhomogeneous".[8]

NCDC experts produced the homogenized data records by correcting for previously-documented errors and newly-identified gross inconsistencies from quality-control checks, by filling in missing data to ensure spatial (*i.e.* to other highly-correlated locations) consistency, but most importantly by correcting for the temporal inconsistencies which make the records inhomogeneous. The most serious inhomogeneities tend to be station relocations and daily observing schedule changes (mentioned above in the NCDC documentation), but modification of the environment of the observation site, either abruptly or over a long period of time (like paving an adjacent area or encroaching development respectively) can either mask or falsely indicate a pervasive climate change.

Artificial biases in the records from identified inhomogeneities are corrected by NCDC to the recent record, because it is the relevant part of the record for forecasting (the use to

[8] From the internal report by NCDC scientists documenting the production of the "homogenized" records.

which NWS puts the homogenized data) and planning (including for rate-making purposes). Consequently, inhomogeneity adjustments tend to be minor or non-existent for the last few decades, so they have practically no impact on normals based on shorter-term averages (discussed in detail next). In contrast, these bias adjustments are critical to precise estimation of how current climate is trending, particularly the slope of the hinge fit. Lastly, most (if not all) of the corrections used in the homogenized records after 1980 ultimately will be used by NCDC to produce the next generation (1981-2010) 30-year normals. Given these considerations, use of the original records to track the climate would be misleading and not productive.

Q. IN ADDITION TO THE HINGE FIT, WHAT IS THE OTHER MAIN ALTERNATIVE YOU HAVE EXAMINED FOR TRACKING CLIMATE CHANGES?

A. Another approach commonly proposed for tracking changing climate involves use of averaging periods shorter than 30 years.

Q. HAS YOUR RESEARCH LED TO ANY CONCLUSIONS ABOUT THE USE OF SHORTER-TERM NORMALS?

A. Yes, because of climate change, in almost all instances shorter-term normals will be superior to 30-year normals. However, my research also has shown that direct analyses from data to determine the best averaging period are very unstable; i.e. extremely sensitive to the particular data sample. The shorter the averaging period is, the greater the instability. This feature was, in fact, a principal motivation for originally adopting normals based on a 30-year period. One of the objectives of my statistical analysis and research was to assess how to determine the best averaging period as well as its expected error in estimating the current climate. I used similar methods to assess the performance of the hinge model and fit.

Q. WHAT OBJECTIVE OR INFORMATION DO YOU SEEK WHEN YOU DETERMINE THE PERFORMANCE OF A TEMPERATURE NORMAL?

A. To reiterate, my main goal here is to determine the best estimate for what the current year's climate is, so different methods are assessed based on how well they do this. The CPC's focus, however, is on next year, but the assessment methods I employ are just as applicable for this target. Further, conclusions about a method's relative performance in describing the current climate can be applied for describing next year's also.

In the context of my stated objective, we know that a 30-year normal will provide a relatively stable estimate, but under conditions of a warming climate, with certainty, will produce a best estimate that will be cold-biased. For parts of MGE's service area I estimate that this cold bias for NCDC 1971-2000 normals could be as much as 3 degrees Fahrenheit for the coldest months of the winter. In other words, the 1971-2000 winter normal for Springfield Regional Airport (for example) is probably more appropriate for the current climate at Kansas City International with Springfield being correspondingly warmer. Further, substantial evidence supports the conclusion that the North American normal temperature increase reflects global increases and both the global and North American increases have been relatively steady over the last several decades. This implies that the most recent 30-year average temperature for North American locations is likely more representative of the climate about 15 years ago than the climate today. With a steadily warming climate, a shorter period average, say 20 years, intuitively would seem to be a better choice for calculating a normal than a 30-year period. This is because such a normal will be most representative of the climate just 10 years ago, rather than 15 years ago as is the case with the 30-year normal. But neither the 30-year normal nor the 20-year normal is appropriate where the data shows a substantive warming trend, as is the case for much of the United States (and Missouri) in winter, because both will be unacceptably cold-biased.

Q. THEN WHY NOT USE A VERY SHORT-PERIOD NORMAL, LIKE A 5-YEAR AVERAGE, TO MINIMIZE THE COLD BIAS?

A. A five-year normal will have a much smaller cold bias than a 20- or 30-year normal if the climate is warming, so the most recent five-year normal might be a more accurate predictor of next year's conditions than a 30-year normal for Missouri. However, shorter-period averages are also much more sensitive than the longer-period averages to unusually cold and warm winters that occur from time to time because of climate noise (independent of the overall warming trend). These outlier winters tend to average out in the longer-period normals, but lead to somewhat large year-to-year changes in the shorter-period averages as these normals are updated each year (by adding the data from the just-completed year and removing the data from the earliest year in the period). This lack of consistency in year-to-year values makes large errors in estimates of next year's conditions common, offsetting any advantage from the smaller cold bias.

A good illustration of this last point is the recent NDJFM temperature record for Missouri shown on p. 27 of this testimony. Because there has been a several-decade warming trend (the green line), recent 5-year averages collectively are warmer than earlier in the record and overall track this change. However, individually the 5-year normals exhibit considerable instability as estimates of the changing climate. For example, there is a large decrease in value (37.8 to 37.2 deg F; an increase of 90 HDDs for NDJFM) when the 5-year average is updated from 2000-2004 to 2001-2005, followed by a much larger increase (37.2 to 38.8 deg F; a decrease of 240 HDDs) in the update from 2001-2005 to 2002-2006. This inconsistency makes 5-year normals unacceptable for use with Missouri winter temperatures.

Q. WHAT THEN DETERMINES THE BEST AVERAGING PERIOD FOR A NORMAL?

A. The best averaging period for use as a normal in a warming climate will be somewhere between 30 and 5 years and represent a balance between the cold biased, but stable longer-period estimates and the relatively unbiased, but outlier-sensitive shorter-period estimates. The averaging period representing the best tradeoff will depend on the strength of the warming trend and characteristics of the climate noise; the length of the period has to be long enough so that a single year with extreme temperatures has minor impact, but short enough to reflect the recent trend.

This best compromise is the OCN, one of the two methods recommended in the 2007 paper. Calculations with the eight weather station records used in the previous figure (representative of MGE's service area)[9] and the results of my research suggest that the OCN is around 15 years for the eight service area stations collectively (as in all normals

[9] The stations are Carrollton, Joplin, Kansas City International Airport, Lee's Summit, Sedalia, Springfield, St. Joseph, and Warrensburg.

calculations, the results for individual weather stations vary somewhat, but average 15 years as well). For the eight locations as a group, the expected standard error using 30-year normals will be about double that using the shorter-period averages. In other words, for these stations, an OCN of around 15 years is expected to have about half the error of a 30-year normal. In using the full 30 years, the error introduced because temperatures have increased over the whole period more than negates the reduction of the error from adding the additional years.

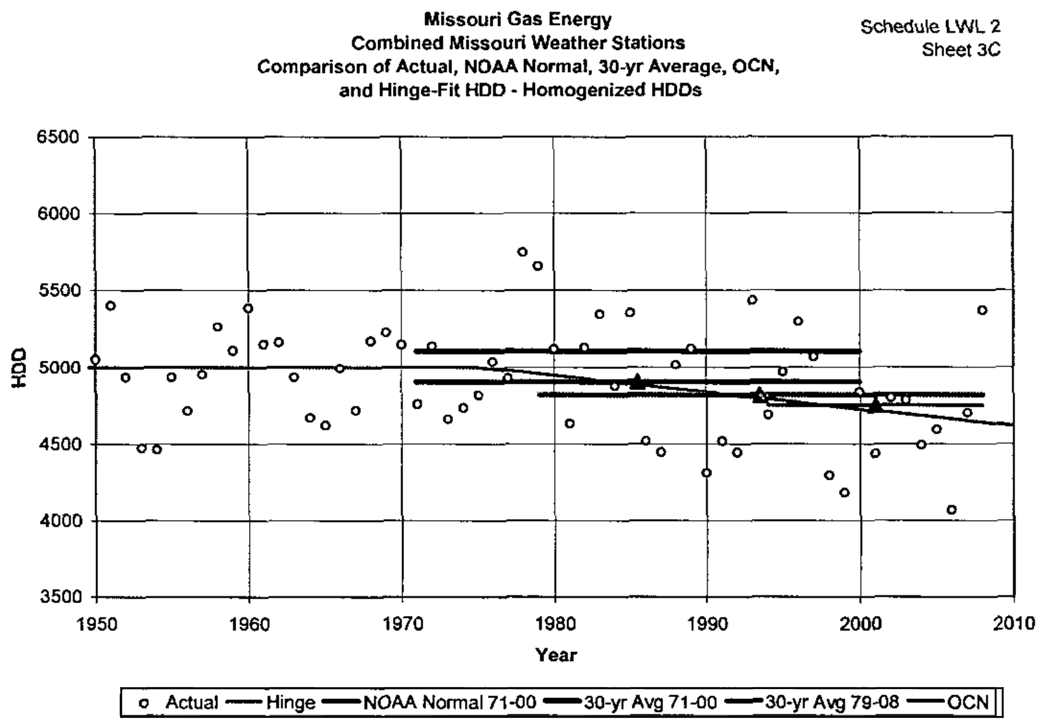
Q. IS THERE A BETTER CHOICE THAN OCN FOR CALCULATING MISSOURI NORMALS?

A. For MGE's gas service territory, my research suggests an even more accurate choice than OCN exists; namely, finding the least-squares fit of the "hinge" model to the data (like in the example shown above) and using the most current point on the upward trend (in average temperature, downward trend in HDDs) part of the hinge as the best estimate for the current climate. This would involve determining the slope of the 1975-2008 trend line portion of the hinge, and then using that slope to determine the temperature during the test year. If desired, the slope could be extended to the first year under new rates, or even the year after that. The hinge technique uses much *more than 30 years of data*, including pre-1975 data that serves to reduce the error in estimating the temperature trends over the last several decades. In effect, it eliminates the weakness of the OCN, which always involves a bias towards a past climate, in favor of a bias towards current trends. Trends for most of the eight locations I examined to represent MGE's service area, as well as their collective trend, are large enough to ensure that the hinge estimate will have a smaller expected error than that of the OCN

Q. CAN YOU SUMMARIZE THE RELATIVE ERRORS FOR DIFFERENT METHODS FOR CLIMATE NORMALS WHEN THE CLIMATE IS CHANGING, LIKE IT IS IN MISSOURI?

A. Yes, I can do this with a graph of yearly total Heating Degree Days ("HDDs") from 1950 to the present averaged over the eight study locations cited above. Because winter temperatures in Missouri have been increasing, HDDs have been decreasing, so the fitted hinge trend for HDDs in the graph should point downward instead of upward as it does in the temperatures graph. Horizontal lines are also drawn on the graph to represent the calculated 15-year OCN (blue line), the most recent 30-year average (orange line), the calculated 1971-2000 average (purple line) and the average of the published NOAA 1971-2000 averages (red line).[10]

[10] The most recent reported NOAA normals are for the period 1971-2000, and were reported by the agency in 2003. Therefore, the net warming experienced in Missouri from 2001-2008 will not be reflected in NOAA normals until the year 2013, assuming no change in NOAA's reporting process.



Notice first how the four time-average estimates successively misrepresent the last ten years more and more as the time period varies, where the 15-year OCN is the least misleading, and the NOAA-convention normals are the most misleading of the four. Clearly, the most representative and best estimate is the endpoint of the hinge trend, which splits the ten most recent HDDs in half.

Next, note on the graph that triangles are placed at the middle-years of all but the NOAA time-average methods. Recall in earlier discussion that for a steadily changing climate, these midyears should be where the respective methods are most representative. For example, if you average 30 years during a period of steadily increasing temperatures, then the average should be warmer than most of the years in the first half of the period and colder than most of them in the second half. All three of the triangles (for time-averages calculated directly from the data) lie on or very close to the hinge trend line, providing considerable confidence that the hinge is accurately representing changing normals in MGE's gas service territory.

OVERVIEW AND RECOMMENDATIONS

Q. PLEASE REVIEW THE ALTERNATIVES TO 30-YEAR WEATHER NORMS YOU HAVE CONSIDERED.

A. Let me now step back and review the alternatives for Missouri (specifically MGE's service area) and their pros and cons:

(1) Trends, likely tied to global scale changes, have been and will likely continue to be a source of considerable error when 30-year normals are used to estimate current and immediate future temperature. If these normals are only updated every 10 years, following conventional NOAA practice, the error quickly becomes overwhelming in the intervening period between updates. Thirty-year normals produce estimates under current circumstances that are always biased to at least 15 years ago.

(2) Use of OCN estimates (around 15-year averages) will reduce estimation error from the most recent 30-year normal by a factor of about two, because it reduces the bias of estimates to as little as 7 to 8 years ago. The OCN's error reduction from the use of published NOAA normals will be much greater. OCN is a simple intuitive step from use of the past 30-years.

(3) An even better choice for much of Missouri is use of the hinge fit, because it uses a long record (up to almost 60 years here versus 30 or fewer years) to reduce the error in trend estimates and it also removes the bias to past climates inherent in the OCN and 30-year normal methods.

(4) Both the OCN and hinge fit methods are relatively simple to implement and routine to compute. Both will produce estimates with similar expected error in all instances, but the hinge fit will outperform OCN for most of the locations in the service area. Both techniques may be available from NOAA within the next year or so and likely will be routinely updated.

Q. DO YOU HAVE A RECOMMENDATION FOR THE COMMISSION?

A. Yes. Since the hinge fit method is more accurate and reliable than 30-year normals and at least as accurate as OCN everywhere in MGE's service area, it should be adopted by the Commission in this Docket instead of the 30-year normals.

Q. HAVE YOU APPLIED YOUR RECOMMENDATIONS TO THE HISTORICAL WEATHER DATA FOR MISSOURI?

A. Company witness Mr. Larry W. Loos has applied my recommendations to calculate the expected weather in 2009 for MGE's service territory in Missouri. The eight-station example of different methods shown above is extracted from his exhibits.

Q. DOES THIS COMPLETE YOUR DIRECT TESTIMONY?

A. Yes.

BEFORE THE PUBLIC SERVICE COMMISSION

OF THE STATE OF MISSOURI

In the Matter of Missouri Gas Energy's Tariff Sheets Designed to Increase Rates for Gas Service in the Company's Missouri Service Area.	))))	Case No. GR-2009-____

AFFIDAVIT OF ROBERT E. LIVEZEY

STATE OF MARYLAND)
) ss.
COUNTY OF MONTGOMERY)

Robert E. Livezey, of lawful age, on his oath states: that he has participated in the preparation of the foregoing Direct Testimony in question and answer form, to be presented in the above case; that the answers in the foregoing Direct Testimony were given by him; that he has knowledge of the matters set forth in such answers; and that such matters are true and correct to the best of his knowledge and belief.

Robert E. Livezey
ROBERT E. LIVEZEY

Subscribed and sworn to before me this 1st day of April 2009.

Notary Public

IGOR CHERNYAK
NOTARY PUBLIC
MONTGOMERY COUNTY
MARYLAND

My Commission Expires: MY COMMISSION EXPIRES JULY 13, 2012

Estimation and Extrapolation of Climate Normals and Climatic Trends

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ABSTRACT

WMO-recommended 30-yr normals are no longer generally useful for the design, planning, and decision-making purposes for which they were intended. They not only have little relevance to the future climate, but are often unrepresentative of the current climate. The reason for this is rapid global climate change over the last 30 yr that is likely to continue into the future. It is demonstrated that simple empirical alternatives already are available that not only produce reasonably accurate normals for the current climate but also often justify their extrapolation to several years into the future. This result is tied to the condition that recent trends in the climate are approximately linear or have a substantial linear component. This condition is generally satisfied for the U.S. climate-division data. One alternative [the optimal climate normal (OCN)] is multiyear averages that are not fixed at 30 yr like WMO normals are but rather are adapted climate record by climate record based on easily estimated characteristics of the records. The OCN works well except with very strong trends or longer extrapolations with more moderate trends. In these cases least squares linear trend fits to the period since the mid-1970s are viable alternatives. An even better alternative is the use of "hinge fit" normals, based on modeling the time dependence of large-scale climate change. Here, longer records can be exploited to stabilize estimates of modern trends. Related issues are the need to avoid arbitrary trend fitting and to account for trends in studies of ENSO impacts. Given these results, the authors recommend that (a) the WMO and national climate services address new policies for changing climate normals using the results here as a starting point and (b) NOAA initiate a program for improved estimates and forecasts of official U.S. normals, including operational implementation of a simple hybrid system that combines the advantages of both the OCN and the hinge fit.

1. Introduction

Climate services of different countries provide customers with statistical information about climatic variables (mainly at the surface) that is based on long-term observations at meteorological stations. This statistical information mainly consists of parameters of the statistical distribution of climatic variables. The most important of these parameters are climatic normals, which are considered to be official estimates of the expected values of climatic variables. The importance of normals derives from their use as a major input for an enormous number of critical societal design and planning purposes.

Because of the widespread need for representative

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normals along with other climate statistics, it is crucial that climate services deliver the best estimates possible. This is universally not the case, however; currently there are either no or suboptimal published estimates of the *current* climate, that is, the expected values of climatic variables today, at time and space scales relevant to the myriad applications for which they are needed. The reason for this is threefold:

1) The contemporary climate is changing at a pace rapid enough to already have important impacts. Climate statistics, including normals, are nonstationary. In the case of U.S. climate divisions, there are many instances in which linear trend estimates (discussed later) yield changes in seasonal temperature and precipitation normals over the last 30 yr that are between 1 and 3 standard deviations of the residual variability. Examples are presented in Fig. 1—note in particular the January–March (JFM) temperature trends in the western United States and October–December precipitation trends in the south central United States. The existence of these trends is one of two sources [the other is El Niño–Southern Oscillation (ENSO) variability] of virtually all of the skill inherent in official U.S. seasonal forecasts, because these forecasts are referenced to the official 1971–2000 U.S. normals (Livezey and Timofeyeva 2007, manuscript submitted to *Bull. Amer. Meteor. Soc.*). In fact, it is impossible to exploit optimally the ENSO signal in empirical seasonal prediction without properly accounting for the time dependence of normals (Higgins et al. 2004).
2) Current physical climate models cannot credibly replicate the statistics of today's climate at scales needed for practical applications, because they cannot credibly replicate recent past climates at these resolutions. These models seem to reproduce the time evolution of the global mean annual temperature well but often fall far short for seasonal mean temperatures at subcontinental and smaller spatial scales at which the information can be practically applied (Knutson et al. 2006). The situation is worse for replication of the evolving statistics of the precipitation climate. We consequently are not in a position to develop accurate estimates of current normals and other statistics through generation of multiple modeled realizations of the climate. However, dynamical climate models may facilitate the development and testing of competing empirical approaches (see section 4).
3) Since the early 1990s, little research and development attention has been devoted to finding improved alternatives to existing (and often misapplied) empirical approaches for estimation and extrapolation of normals, which include linear trend fitting and the so-called optimal climate normal (OCN; Huang et al. 1996; Van den Dool 2006) used in seasonal prediction by the U.S. National Weather Service (NWS) of the National Oceanic and Atmospheric Administration (NOAA).

The consensus expectation of the climate community is that the global climate will continue to change, and therefore the fundamental problem emphasized here will not disappear. In the meantime a great deal of research attention and resources are being devoted worldwide to improvement of global climate models, but it will take many years before these models can be leveraged directly for monitoring current climate at time and space scales practical for applications. In contrast, viable alternatives to current empirical techniques do exist for estimation and extrapolation of time-dependent normals and other climate statistics. Therefore, they should be explored and adopted, including for official use to supplant current practices.

The intent of this paper is to highlight the problem of empirical estimation and extrapolation of time-dependent climate statistics, with a particular emphasis on normals, to raise the problem's profile and encourage increased attention to it in the applied climate community, and to effect changes in official practices. To meet these goals, we will analyze and compare the expected error of four current approaches (one introduced here for the first time) for estimation and extrapolation, through the use of a statistical time series model appropriate for many meteorological time series.

The three current methods are 30-yr normals that are officially recomputed every 10 yr (e.g., for 1961–90, 1971–2000) in the United States by the NOAA National Climatic Data Center (NCDC) and are traditionally available 2–3 yr later (historically in 1963, 1973, . . . , 2003), the above-mentioned OCN, and least squares linear trend fitting. The fourth approach is a modification of least squares linear fitting to model more closely the observed characteristics of the likely underlying cause of rapidly changing normals—namely, global climate change. In the first two of the four techniques, extrapolations are made by assigning the latest computed value to future normals, but in the latter two they are made by extending the linear trend into the future.

In the presence of strong, dominantly linear trends largely attributable to global climate change (like those characterizing North America in the winter and spring), it is intuitive that each successive approach of the four listed above (if appropriately applied) should outper-

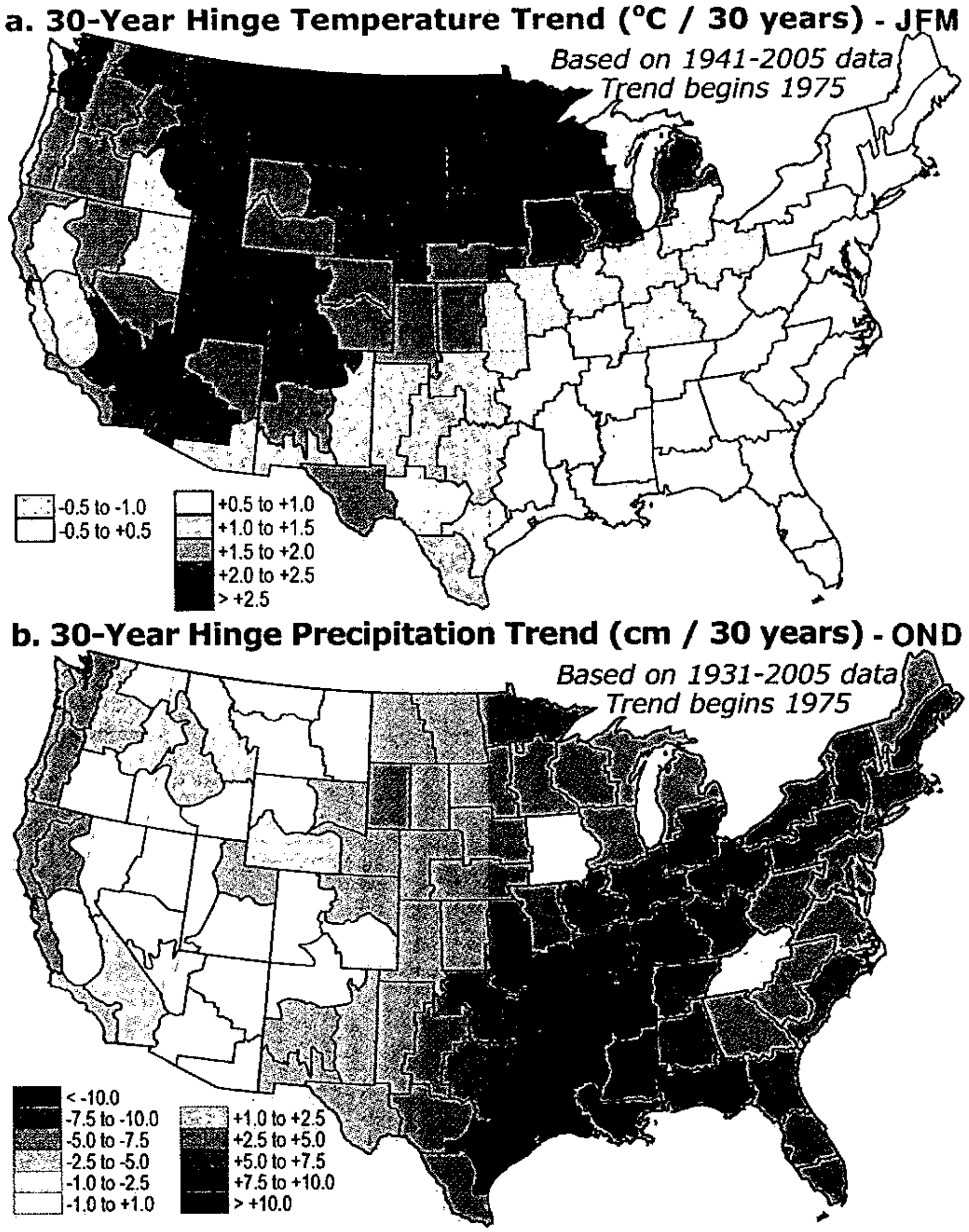

FIG. 1. Trends in (a) January–March mean surface air temperature and (b) October–December mean precipitation normals for 102 U.S. climate divisions. Trends are for the 30 yr ending in 2005 and are estimated using a technique described in section 3b.

form those preceding it. The analysis here will provide an objective, quantitative basis for this intuition. Problems associated with least squares linear trend fitting and its misapplication will also be discussed. The results here and a few other basic precepts can constitute a starting point for best practices for normals and trends for working climatologists.

Following the comparative analysis, the paper contains a brief discussion of nonlinear and adaptive trend estimation methods. An overview of recent advances in the treatment of two other important nonstationary components in climate statistics, the diurnal and annual cycles, is included in an appendix. The paper concludes with summary remarks and recommendations.

2. Trend-related errors in estimates of climatic normals

Let us consider a time series of annual (or monthly for specific month, etc.) values of a meteorological variable $y(t)$ that consists of two independent components:

$$y(t) = Y(t) + y'(t). \quad (1)$$

Time t in this case is in years, $Y(t)$ is the time-dependent expected value of $y(t)$ (e.g., climatic trend), and $y'(t)$ is climatic noise described by a zero-mean stationary red-noise random process with variance σ^2 and 1-yr autocorrelation g. Let us assume that the actual trend in expected value $Y(t)$ is linear with known constant a and b in the expression

$$Y(t) = a + bt. \quad (2)$$

The trend parameter b can be expressed in relative units of sigma per year as $\beta = b/\sigma$. Instead of the actual $Y(t)$ we always use its estimate $\tilde{Y}(t)$ derived from observed data. The accuracy of $\tilde{Y}(t)$ depends on the method by which it is estimated. Let $\delta^2(t)$ be the mean-square error of estimated expected value $\tilde{Y}(t)$ and $\eta(t)$ be the mean (expected) square relative (to the climatic noise; i.e., scaled by σ) error:

$$\delta^2(t) = \overline{[Y(t) - \tilde{Y}(t)]^2} \quad \text{and} \quad \eta(t) = \delta^2(t)/\sigma^2. \quad (3)$$

In the remainder of the article, $\eta(t)$ will be referred to as the "error" for simplicity.

a. Thirty-year normals

The traditional approach to climate normals will be evaluated first. A comprehensive historical analysis of the evolution of the definition of climatic normals can be found in Guttman (1989). The normals, recommended by the World Meteorological Organization (WMO), are 3-decade averages recomputed each 30 yr (for surface variables only). However, NCDC and many other climatic centers voluntarily recompute them each decade. If this practice survives during the next few years, the current 1971–2000 normals will be replaced by 1981–2010 normals as soon as they are computed and released, likely by 2013.

A 30-yr average was long considered an acceptable trade-off between excessive sampling errors from climatic noise for shorter averages and unacceptably large changes in the climatic normal $Y(t)$ over the averaging period for longer averages. A time average will generally approximate a monotonically changing normal that is best near the midpoint of the averaging interval, with error increasing toward the beginning and end of the interval. However, if the change is slow then it will still constitute a good estimate over the entire span, in this case 30 yr. Here we will quantify the way faster-changing climatic normals compromise the acceptability of the 30-yr average trade-off. In section 2b, the same problem will be addressed for other averaging periods updated annually, that is, moving averages, and the results will be applied to assess the OCN method.

There are two major categories of users of the WMO normals. The first category of these users is forecasters, who predict (in some fashion) climate anomalies in the future for time intervals from a few weeks to 1 yr. The predicted climate anomalies must be expressed as anomalies from the official (i.e., past) normals. Because the climate is nonstationary, however, a prediction of the normal is necessary as well and becomes a key part of the forecast and a source of much of its skill (or lack thereof). The other user category needs climatic normals for more distant periods of time (on the order of 10 yr) for planning and design purposes. Consider the case in which all of these consumers use the official normals for the next decade, until new normals can be computed and released.

Here an N-yr average of the observed $y(t)$ is the estimate of its climate normal. Let $\tau = t - t_0$, where t_0 is the last year of the averaging period. Using (2) and (3), it is straightforward to obtain

$$\eta(N, g, \beta, \tau) = \eta_a(N, g) + \eta_b(N, \beta, \tau), \quad (4)$$

where $\eta_a(N, g)$, the contribution to the error η from the sampling error of averaging red-noise residuals $y'(t)$ over N yr, is

$$\eta_a(N, g) = (1 + g)/[1 + g + (N - 1)(1 - g)], \quad (5)$$

and $\eta_b(N, \beta, \tau)$, the contribution to η related to the known trend $\beta = b/\sigma$, is

$$\eta_b(N, \beta, \tau) = \{\beta[(N - 1)/2 + \tau]\}^2. \quad (6)$$

The expression for the sampling error (5) is from Polyak (1996). The expression for trend-related error (6) follows from the derivation and represents systematic, not random, error. It is equal to zero at the mid-interval time $t^* = t_0 - (N - 1)/2$ and increases in both directions from this point proportionally to the squares of trend b and time increment $t - t^*$.

The error $\eta(N, \tau)$ of WMO normals ($N = 30$ yr), computed from (4)–(6) for different β and g, is given in Table 1 for $\tau = 0$ and $\tau = 10$ yr. As noted in the introduction, the range of β in Table 1 has been observed for U.S. climate-division seasonal mean tem-

TABLE 1. Theoretical estimates of $\eta(N, g, \beta, \tau)$, the expected mean-square relative [i.e., $\delta^2(t)/\sigma^2$] error of WMO normals at the end of an N = 30 yr period of averaging (τ = 0) and 10 yr later (τ = 10 yr) for different linear trends $\beta = b/\sigma$ and lag-1 correlations g in climatic records. Values equal to or greater than 0.25 are shown in boldface.

	g = 0		g = 0.1		g = 0.2		g = 0.3		g = 0.5	
	τ = 0	τ = 10	τ = 0	τ = 10	τ = 0	τ = 10	τ = 0	τ = 10	τ = 0	τ = 10
β = 0	0.03	0.03	0.04	0.04	0.05	0.05	0.06	0.06	0.09	0.09
β = 0.01	0.05	0.09	0.06	0.10	0.07	0.11	0.08	0.12	0.11	0.15
β = 0.02	0.12	**0.27**	0.12	**0.28**	0.13	**0.29**	0.14	**0.30**	0.18	**0.33**
β = 0.03	0.22	**0.57**	0.23	**0.58**	0.24	**0.59**	**0.25**	**0.60**	**0.28**	**0.63**
β = 0.05	**0.56**	**1.53**	**0.57**	**1.54**	**0.57**	**1.55**	**0.59**	**1.56**	**0.62**	**1.59**
β = 0.10	**2.14**	**6.04**	**2.14**	**6.04**	**2.15**	**6.05**	**2.16**	**6.06**	**2.20**	**6.10**

perature and precipitation. Calculations of g for residuals from these estimated trends range from near 0 to greater than 0.5; therefore Table 1 spans real-world scenarios.

Different applications require different accuracy in the trend estimates. In the absence of an econometric approach in which a cost function limits our natural desire to improve the accuracy of information any further, however, we can adopt the minimal requirement that the error should not exceed a traditionally acceptable value that corresponds to standard error $\delta \leq 0.5\sigma$. This formal criterion is often used in statistical meteorology (Vinnikov 1970). It corresponds to $\eta \leq 0.25$, which will be referenced throughout subsequent discussions.

Note first in Table 1 that the errors $\eta(g, \beta, \tau)$ are not noticeably dependent on g, the measure of redness in the residual time series, but rather on trend β and on τ, where τ is the amount of time after the last year of observations used to compute normals. The error in "persisting" WMO normals exceeds the acceptable limit for $b \geq 0.3\sigma$ (10 yr)$^{-1}$ for almost all τ [and for τ = 10 yr and $b \geq 0.2\sigma$ (10 yr)$^{-1}$]. As soon as $b \geq 0.2\sigma$ (10 yr)$^{-1}$ and τ is close to 10 yr, the WMO normals should not be used for computing climatic anomalies. Except for weak underlying trends, the error is already unacceptable when the 30-yr normal is released (between τ = 2 and 3 yr).

An attempt to solve this problem motivated scientists at NWS's Climate Prediction Center (CPC) to further develop and implement the OCN. OCN, introduced pragmatically and empirically, has never been explained in sufficiently simple terms but has not been used much outside of CPC. The error associated with OCN estimation and extrapolation will be evaluated next.

b. Optimal climate normals

The first empirical attempts to find the optimal length of the averaging period for hydrological and meteorological data were by Beaumont (1957) and Enger (1959). As a criterion, they used the variance of the difference between N-yr averages and values of climatic variables 1 yr ahead. Later, Lamb and Changnon (1981) estimated the "best" temperature normals for Illinois observed temperature and precipitation using as a criterion the mean absolute value of the same differences. The CPC criterion (applied to 3-month average surface temperatures and precipitation) is based on the maximum of a correlation-like measure between N-yr averages and values 1 yr ahead over the verification period (Huang et al. 1996). The CPC group showed that their criterion produced practically the same results as those used by Beaumont (1957) and Enger (1959). Simple analysis shows that all of these criteria are based on similar definitions of a measure of error in climatic normals when compared with the time-dependent expected value. In fact, the theory of OCNs can be derived from the same simple model (3)–(5) for the error in climate normals.

Expression (4) for the error in the expected value estimate obtained by averaging observed $y(t)$ for N consecutive years $\eta(N, g, \beta, \tau)$ is a sum of two components. The first one, $\eta_a(N, g)$, decreases monotonically with increase in N. This is the expected sampling error from the climatic noise—its decrease with increasing N is what is expected intuitively. The second component, $\eta_b(N, \beta, \tau)$, increases as N increases if the trend $\beta \neq 0$. It is the expected deviation of the N-yr average from the trend line at the end of the averaging interval and beyond, which must increase with N because the number of years from the midpoint of the interval increases. As a result, the error $\eta(N, \tau)$ has a minimum $\eta_{\text{optimal}}(N, g, \beta, \tau)$ at $N_{\text{optimal}}(g, \beta, \tau)$.

Our ability to correctly estimate the climatic anomaly $y'(t_0)$ at the end of the averaging period (τ = 0) and to extrapolate it into the future time, $\tau > 0$, depends on the error in expected value $Y(\tau)$. Optimal climate normals can be defined as the average of the climatic variable for the time interval N_{optimal} that minimizes the

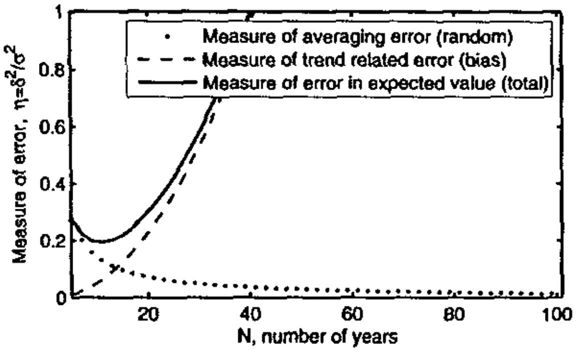

FIG. 2. Optimal climate normals: $\eta(N, g = 0.2, \beta = 0.05, \tau = 0)$—the error of expected value $Y(\tau = 0)$ at the very end of an averaging time interval of N yr for a specified linear trend $\beta = 0.05$ and lag-1 autocorrelation $g = 0.2$ (solid line). Dotted and dashed lines show separately the averaging $\eta_a(N, g = 0.2)$ and the trend-related $\eta_b(N, \beta = 0.05, \tau = 0)$ components of the error.

error $\eta(N, g, \beta, \tau)$ in estimates of expected value $Y(\tau)$. Estimates of N_{optimal} for given g, τ, $\beta \neq 0$ can be obtained from the condition

$$\eta(N, g, \beta, \tau) = \text{minimum}, \tag{7}$$

and then substituted into (4)–(6) to compute η_{optimal}.

For illustration, consider a process with lag-1 correlation $g = 0.2$ and trend $b = 0.05\sigma\ \mathrm{yr}^{-1}$. These parameters could belong to time series of wintertime seasonal mean surface air temperatures for a number of western U.S. climate divisions. Figure 2 shows the dependence on N, the number of years of observations averaged to obtain the estimate of $Y(t_0)$, of $\eta(N, g, \beta, \tau)$ and its components $\eta_a(N, g)$ and $\eta_b(N, \beta, \tau)$ for $\tau = 0$. The two components respectively are the sampling error from the climatic noise (decreasing with N) and the error from the diverging trend (increasing with N). In this example, the function has a minimum at $N = N_{\mathrm{optimal}} \approx 11$ yr.

Forecasts at CPC and other climate prediction centers do not, in general, exceed 1-yr lead ($0 \leq \tau \leq 1$ yr). Estimates of $N_{\mathrm{optimal}}(g, \beta, \tau)$ and $\eta_{\mathrm{optimal}}(g, \beta, \tau)$ for $\tau = 0$ and 10 yr and for realistic ranges of g and β, $\beta \neq 0$, are given in Table 2. The estimates for $\tau = 1$, not shown here, are very close to those for $\tau = 0$. Note the following from Table 2:

1) The optimal period of averaging N_{optimal} and its associated error η_{optimal} depend more on β than on g except for large g; that is, it is dominated by trend rather than weak red noise. Thus, if the climatic trend has a seasonal cycle and geographical pattern, so will the optimal period of averaging.
2) For trends as large as $b = 0.1\sigma\ \mathrm{yr}^{-1}$ the optimal period of averaging N_{optimal} is very short (from 6–7 yr for $\tau = 0$ to 3 yr for $\tau = 10$ yr) and the error η_{optimal} of OCN exceeds the acceptable limit of 0.25 for almost all τ shown. For $b = 0.05\sigma\ \mathrm{yr}^{-1}$, $\tau > 0$, and $g > 0.2$, the error also exceeds 0.25.
3) The errors related to the climatic trend in the OCN estimates of $Y(t_0)$ are systematic, not random. Such errors should be treated differently than random errors.
4) The WMO-recommended 30-yr averaging (Table 1) is close to the OCN for very weak climatic trends ($b = 0.01\sigma\ \mathrm{yr}^{-1}$), and the error is identical within the precision of both tables. Because OCN is updated annually, however, it is the preferred choice even with very weak underlying trend, but not as practiced at CPC (see the paragraph after next). As a consequence, OCN has two advantages over conventional practice: N_{optimal} adjusted to the situation and immediate updates through the last year.

Thus the WMO technique is a good treatment for very weak climatic trends, and the OCN technique is good for modest to medium trends with the lead τ relatively small, but neither has acceptable error for strong trends and longer leads.

TABLE 2. Optimal climate normals technique: analytical theoretical estimates of N_{opt} (yr) and η_{opt} (where opt denotes optimal) for $\tau = 0$ and 10 yr and different lag-1 correlation coefficients g and trends β in climatic records. Values equal to or greater than 0.25 are shown in boldface.

		$g = 0$		$g = 0.1$		$g = 0.2$		$g = 0.3$		$g = 0.5$	
$\beta = b/\sigma$	Year	N_{opt}	η_{opt}	N_{opt}	η_{opt}	N_{opt}	η_{opt}	N_{opt}	η_{opt}	N_{opt}	η_{opt}
$\beta = 0.01$	$\tau = 0$	27.5	0.05	29.2	0.06	31.1	0.07	33.1	0.08	38.2	0.11
	$\tau = 10$	22.1	0.09	23.7	0.10	25.5	0.11	27.4	0.12	32.2	0.15
$\beta = 0.02$	$\tau = 0$	17.4	0.08	18.5	0.10	19.6	0.11	20.8	0.13	23.7	0.17
	$\tau = 10$	12.6	0.18	13.5	0.19	14.5	0.21	15.5	0.23	18.1	**0.29**
$\beta = 0.03$	$\tau = 0$	13.4	0.11	14.1	0.12	15.0	0.14	15.8	0.16	17.9	0.22
	$\tau = 10$	8.9	**0.29**	9.5	**0.31**	10.2	**0.33**	10.9	**0.36**	12.5	**0.43**
$\beta = 0.05$	$\tau = 0$	9.6	0.15	10.1	0.17	10.7	0.19	11.2	0.22	12.5	**0.29**
	$\tau = 10$	5.7	**0.56**	6.0	**0.59**	6.4	**0.62**	6.7	**0.66**	7.5	**0.88**
$\beta = 0.10$	$\tau = 0$	6.2	0.23	6.5	**0.26**	6.7	**0.29**	7.0	**0.33**	7.6	**0.42**
	$\tau = 10$	3.0	**1.54**	3.1	**1.59**	3.2	**1.64**	3.2	**1.69**	3.2	**1.81**

As mentioned earlier, OCN is currently used at CPC for short-term climate prediction, $\tau \leq 1$ yr, using empirically, not theoretically, estimated optimal averaging time intervals (for $\tau = 1$ yr) fixed at 15 yr for monthly precipitation and 10 yr for monthly temperatures (Huang et al. 1996; Van den Dool 2006). From Table 2 these averaging periods correspond approximately to those for short-lead cases with $b = 0.03\sigma\ \mathrm{yr}^{-1}$ and $b = 0.05\sigma\ \mathrm{yr}^{-1}$, respectively. As a consequence, the entries in Table 2 are underestimates of the errors of CPC/OCN when underlying trends in precipitation and temperature differ much from these values. More specific, for $\tau = 0$, CPC/OCN will have larger errors than those in Table 2 for all cases except $b = 0.05\sigma\ \mathrm{yr}^{-1}$ and $g = 0.1$ for temperature and $b = 0.03\sigma\ \mathrm{yr}^{-1}$ and $g = 0.2$ for precipitation. Fixed N is more convenient but is inadvisable unless N_{optimal} varies little across a user's applications.

The OCN technique is an attempt to account for the effects of a climatic trend without defining and estimating the trend itself. Consideration will be given next to the use of observed data to estimate climatic trends and to utilize the estimated dependence of expected value on time. Such an approach should work better than the OCN for very strong trends.

3. Time-dependent climatic normals

a. Least squares linear trend

Consider again the same (as above) climatic process $y(t)$ whose random red-noise component has standard deviation σ and lag-1 autocorrelation g. Suppose there is confidence from independent sources that this record has a linear trend in expected value $Y(t) = a + bt$. Using a least squares technique, the unknown parameters a and b and the statistics of their errors can be estimated through use of an analytical solution obtained by Polyak (1979). A summary of the same equations is reproduced in Table 2.1 of the English edition (Polyak 1996). Now the estimates of the expected normal at the end of the interval and beyond are based on the fitted trend line. We can use the same (1)–(3) and (5) equations and definitions as above, but with N now the length of the time interval used to estimate a and b in (2), and with a new expression, different from (6), for trend-related error $\eta_b(N, g, \tau)$, to write

$$\eta(N, g, \tau) = \eta_a(N, g) + \eta_b(N, g, \tau), \tag{8}$$

$$\eta_b(N, g, \tau) = [\sigma_\beta(r + \tau)]^2,\ r = (N - 1)/2, \quad \text{and} \tag{9}$$

$$\sigma_\beta^2 = (1 + g)/\langle r\{2[r + g/(1 - g)] + (1 - g)(r - 1)(2r - 1)/3\}\rangle. \tag{10}$$

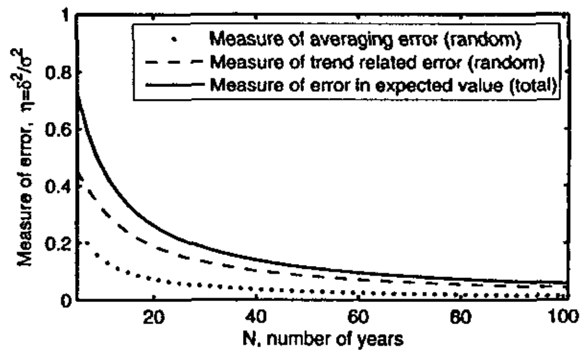

FIG. 3. Estimates of $\eta(N, g = 0.2, \tau = 0)$, the error in expected value $Y(t_0)$ at the end of time interval N yr utilized to estimate parameters of linear trend (black line). Dotted and dashed lines show separately the averaging and the trend-related components of error variance.

As before the first term represents sampling error associated with estimating the stationary part of the normal. However, now the second term represents the error at the endpoint of the estimation interval and beyond associated with the slope estimation, not the error associated with not accounting for the slope at all.

The values of $\eta(N, g = 0.2, \tau = 0)$, the error in expected value $Y(t_0)$ at the end of time interval N yr [used to estimate the trend in $Y(t)$], are displayed in Fig. 3 (the solid line). Dotted and dashed lines show separately the averaging and the trend-related components of error variance. The first of them (dotted line) is the same as in Fig. 2. It decreases with an increase of N. However, the trend-related error (dashed line) also decreases with an increase of N, because the error in estimating the slope must decrease as the length of the fitted series with the underlying trend increases. Furthermore, unlike before, the trend-related error does not depend on the trend, and as a consequence the total error η is random with no systematic component. We can conclude that the empirically estimated climatic trend $Y(t) = a + bt$ provides sufficiently accurate unbiased estimates of expected value of $Y(t_0)$ for records as short as ~30 yr in the case of $g = 0.2$.

Climatic normals, estimated from observations over a limited time interval, should be useful for predictions beyond the boundaries of this time interval. Given estimated parameters of a linear trend in expected value $Y(t) = a + bt$, we can use the same a and b to find $Y(t_0 + \tau)$, where t_0 is the end of the fitting period N and $t = t_0 + \tau$ is some time in the future. Errors in extrapolated $Y(t_0 + \tau)$ increase with increasing τ. Theoretical estimates of the error $\eta(N, \tau)$ for different N, τ, and g are shown in Fig. 4.

For all cases in Fig. 4 with $g < 0.5$, extrapolation of

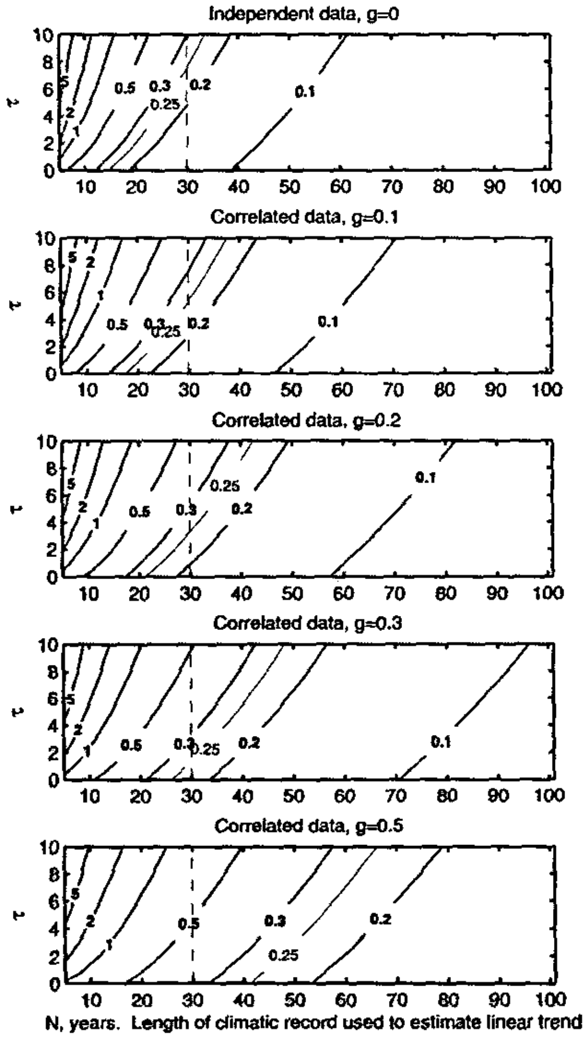

FIG. 4. Estimates of $\eta(N, g, \tau)$, the error for extrapolated expected value $Y(t_0 + \tau)$ beyond the end of time interval of N yr utilized to estimate parameters of linear trend; τ is in years.

TABLE 3. The maximum lead (yr) τ_{max} with acceptable error $\eta \le 0.25$ for different 1-yr lag autocorrelation g and different projections of an underlying linear-trending normal estimated from climate time series models. Results for the hinge fit (trend period is 30 yr, the same as for the linear fit) are for generalized least squares, which yields small gains over the ordinary least squares results from the Monte Carlo experiment.

	τ_{max}			
g	Hinge fit (N = 65 yr)	Linear fit (N = 30 yr)	OCN (β = 0.03)	OCN (β = 0.05)
0.0	14	7	8	3
0.1	10	5	7	2
0.2	7	3	6	2
0.3	4	1	5	1
0.5	—	—	2	—

the linear trend 1 yr into the future estimated from $N \ge 30$ has expected error less than the acceptable value of 0.25. For users of climatic information a decade in the future ($\tau \approx 10$ yr), trends must be estimated from significantly longer ($N \approx 40$–50 yr) climatic records for acceptable precision. In actuality, it is highly questionable that these longer trend fits are viable in practice because of the nature of actual trends discussed next.

As a practical matter, virtually all of the current important temperature trends over the United States (many exceed $b = 0.05\sigma$ yr^{-1}) have occurred over the last 30 yr. As a consequence, the only relevant (to current climate change) parts of Fig. 4 are those with $N \le 30$ yr. Because of the strong dependence on the redness (g) of the residual variability, the results in Fig. 4 preclude accurate multiyear extrapolation except when the 1-yr lag correlation is zero or very small, because N should be constrained to be less than or equal to 30 yr.

It is crucial to account for these considerations in studies focused on the current climate and on modern and future climate changes. In these instances, least squares linear trend fits to the last (prior to 2006) 40–100 or more years of data will generally underestimate recent changes and can distort and misrepresent the pattern of these changes. These problems can be avoided by following some sound practices for linear trend estimation: 1) Linear trends should never be fit to a whole time series or a segment arbitrarily, 2) at a minimum, a plot of the times series should be examined to confirm that the trend is *not* obviously nonlinear, and 3) to the extent possible, the functional form of the trend should be based on additional considerations.

In this context, note that very large scale trends associated with global climate change are approximately linear over the last 30 yr or so but decidedly not over the last 40–70 or more. This fact is the basis for the modified approach to linear least squares that will be examined next. First, however, the relative performance in estimation and extrapolation of normals between the OCN and linear least squares (given an underlying linear trend) will be summarized.

Table 3 shows error thresholds (as a function of redness) expressed as the maximum lead τ (in years) with acceptable error, for 30-yr linear trend fits and the OCN with $b = 0.05\sigma$ yr^{-1} and $b = 0.03\sigma$ yr^{-1}. The table reflects a main conclusion of the last section: that the OCN has acceptable error for modest to moderate underlying linear trends at medium to short leads, respectively. However, it is also clear from Table 3 that 30-yr least squares linear fits (hinge fits are discussed in the next section) substantially outperform the OCN with

$b = 0.05\sigma$ yr^{-1} and are competitive (as long as the autocorrelation in the climate noise is very small) at $b = 0.03\sigma$ yr^{-1}. The OCN's advantage with $b = 0.03\sigma$ yr^{-1} (as reflected in Table 3) in operational CPC practice should be less for every g because of the use of fixed (and suboptimal) averaging periods. Except for very small g, this overestimation of operational OCN τ_{max} will be greater for temperature series than for precipitation because the latter's averaging period (15 yr) is generally closer to the optimal period (Table 2).

The calculations here suggest that 30-yr linear trends are at least as good for operational purposes for all but very modest trends ($b < 0.03\sigma$ yr^{-1}), at least for temperature normals (for precipitation normals, OCN's advantage is lost for only slightly stronger trends). As shown in the next section, a modification to the linear trend fits (based on global climate change considerations) that reduces the trend-related error extends the useable extrapolation range even further.

b. The least squares "hinge"

Very large scale trends (in global, hemispheric, land, ocean, etc., seasonal and mean annual temperatures) associated with global warming are approximately linear since the mid-1970s but decidedly not when viewed over longer periods. In particular, smoothed versions of these series dominantly suggest little change in their normals from around 1940 up to about the mid-1970s (e.g., Solomon et al. 2007).

With the reasonable assumption that the strong trends over North America (and probably elsewhere as well) in the last 30 yr or so are related to global warming, an appropriate trend model to fit to a particular monthly or seasonal mean time series to represent its time-dependent normal is a hingelike shape. This least squares hinge fit is a piecewise continuous function that is flat (i.e., constant) from 1940 through 1975 but slopes upward (or downward as dictated by the data) thereafter: $Y(t) = a$ for $1940 \le t \le 1975$ and $Y(t) = a + b(t - 1975)$ for $t \ge 1975$. The choice of 1975 as the hinge point is based on numerous empirical studies and model simulations that all suggest the latest period of modern global warming began in the mid-1970s. The slope b is insensitive to small changes in this choice.

The hinge shape is clearly the behavior of the JFM mean temperature series for the climate division representing western Colorado (Fig. 5), where the observed series and the ordinary least squares hinge fit are both shown. Western Colorado temperature was selected as an example for Fig. 5 because it has little or no ENSO signal, but to first order the hinge dominantly characterizes the behavior of U.S. climate-division

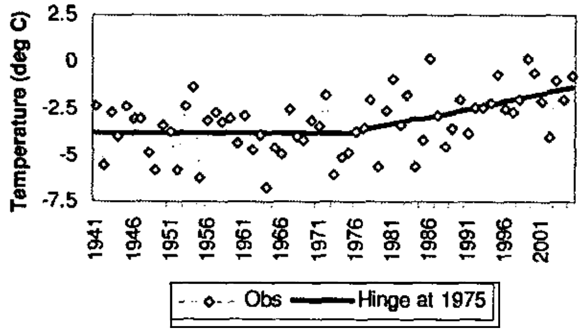

FIG. 5. January–March mean temperatures for western Colorado, and the ordinary least squares hinge fit to the data.

monthly and seasonal mean time series with moderate to strong trends, especially for surface temperatures.

The hinge technique was first (and exclusively) used in 1998 and 1999 by CPC to help to estimate and extrapolate normals for the cold-season forecasts for 1998/99 and 1999/2000, respectively—both winters with a strong La Niña. After the winter of 1997/98, the great El Niño winter, it was determined at CPC that the cold bias in the winter forecast for the western United States was entirely a consequence of failing to account for a warming climate. Based on the work of Livezey and Smith (1999a,b), the warming was associated with global climate change.

The hinge fit was subsequently devised not only to estimate and extrapolate the trends, but to assess more accurately the historical impacts of moderate to strong ENSO events on the United States. This signal separation required the reasonable assumption that ENSO and global change were independent to first order. With this assumption, conventional approaches for estimating event frequencies conditioned on the occurrence of El Niño or La Niña (e.g., Montroy et al. 1998; Barnston et al. 1999) were modified to account for the changing climate as well.

The effectiveness of the hinge-fit method for the JFM 2000 U.S. mean temperature forecast is shown in Fig. 6. The three panels in the figure are conditional mean temperature probabilities using a version of conventional methods (often referred to as composites; Barnston et al. 1999; Fig. 6a); conditional probabilities using the hinge for trend fitting and signal separation (Fig. 6b); and the verifying observations (Fig. 6c). The first steps to construct (Fig. 6b) consisted of hinge fits to the JFM time series through 1999, calculation of JFM residuals from the hinge fits for past La Niñas, 1-yr extrapolations of the fitted slopes, and addition of the La Niña residuals to the 1-yr extrapolations to obtain conditional frequency distributions. After some spatial

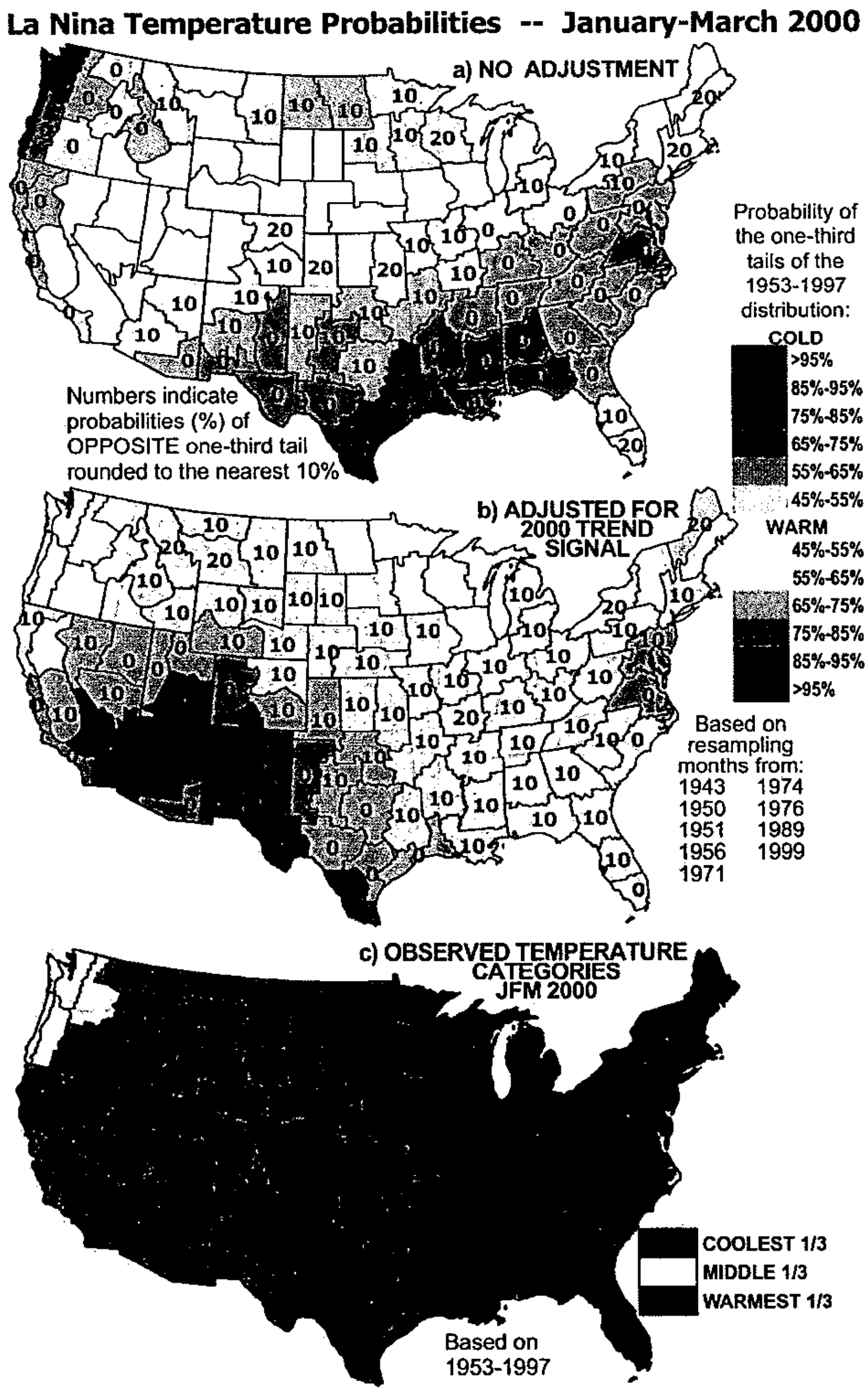

FIG. 6. Probabilities, (a) without and (b) with separate treatment of trend and La Niña, for three temperature categories (above-, near-, and below-normal equally probable for 1953–97 data) of January–March 2000 mean surface air temperatures for 102 U.S. climate divisions, and (c) the corresponding observations.

smoothing, these values were then referenced to three equally probable categories based on 1953–97.

Note the large differences between Figs. 6a and 6b and their implications for JFM and the extraordinary similarity between Figs. 6b and 6c, the forecast and observed conditions. The year 1966 was used as the hinge point in these 1999 calculations; use of a more appropriate mid-1970s point would have produced a forecast with even wider coverage of enhanced probabilities of a relatively warm JFM.

It is clear from CPC's and subsequent experience that composite studies of ENSO impacts that do not attempt to account for important trends are deficient from the outset. There fortunately are seasons/areas of the United States for which recent trends are still weak but the ENSO signature is strong, for example much of the Southeast in the winter (Fig. 1). In these instances the climate analyst can ignore trend to diagnose ENSO-related effects; otherwise trend consideration is a critical first step for useful results, regardless of the methods employed.

Here, to explore hinge-fit expected errors, Monte Carlo simulations are used to assess the reduction in error by using a hinge instead of a straight-line least squares fit. Our expectation is that hinge fits will have smaller overall error, simply because the use of 35 additional years (1940–74) of observations to estimate climate normals in the mid-1970s will constrain the starting value at the beginning of the trend period.

In effect, the hinge approach reduces the usual oversensitivity of least squares linear trend fits to one of the endpoints of the time series. A particularly important example of this problem is the pattern of U.S. winter temperature trends computed from the mid-1970s. The winters of 1976/77 and 1977/78 were unusually warm in the west with record cold in the east. Least squares linear trend fits starting from 1976 or 1977 consequently tend to overestimate warming in the east and underestimate it in the west, leading to maps with far more uniform warming than the pattern in Fig. 1.

Simulated time series 75 yr in length (to represent 1940–2014) were generated by adding random, stationary red noise with standard deviation of 1 and lag-1 autocorrelation g to a constant zero over the first 36 yr (to 1975) and to an upward linear trend with constant slope thereafter. Monte Carlo experiments, each consisting of 2500 simulations, were conducted for $\beta = 0.03$ and g ranging from 0.0 to 0.5. Straight lines and hinges were fit with ordinary least squares to each time series with data spanning 1975–2004 and 1940–2004, respectively. Each fit was then extrapolated linearly to 2014, and its difference from the specified value of the underlying hinge was computed. The results should not depend on slope, and this was confirmed by other calculations.

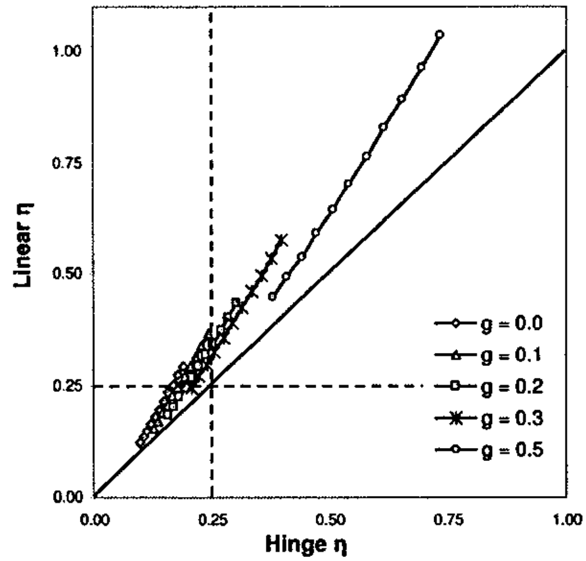

FIG. 7. Error η of climate normal estimates (with $\beta = 0.03$) at leads from zero to 10 yr for ordinary least squares straight-line and hinge fits to modeled climate time series.

Results in the form of error η for both fits at leads $\tau = 0, \ldots, 10$ are displayed in Fig. 7. The error η for the hinge is less than that for the straight-line fit for every point plotted, and its advantage increases with lead and (mostly) the autocorrelation in the residual noise.

Use of generalized least squares for hinge fits should reduce expected errors even further; therefore, these errors were also computed. The gains over the ordinary least squares results in Fig. 7 are small but meaningful, and therefore the generalized least squares results are shown in Table 3. Note that use of the hinge essentially eliminates OCN's advantage for all but $g = 0.5$ (rarely observed in U.S. climate-division data for $\beta \geq 0.03$), and even more so when OCN is implemented in a suboptimal fashion with fixed averaging periods. The results here suggest that a preferred approach would consist of the OCN (with variable averaging period) for cases with weak trends and the hinge for cases with moderate to strong trends. Such a strategy would require hinge fits everywhere first for a preliminary diagnosis of the strength of the trend and the redness of the residual climate noise, to guide the choice of final fits and for case-by-case specification of OCN averaging in weak trend situations, respectively.

As a service to the applied climatology community, maps of hinge-based trends for 3-month mean U.S. climate-division surface temperature and precipitation for 3 nonoverlapping periods, which, along with Fig. 1, span the year, are included in appendix A (a more complete set was available at the time of writing online at http://www.cpc.ncep.noaa.gov/trndtext.shtml). The data used in all of the maps and time series shown here and the reasons for their use are also described in appendix A.

c. Other shapes

Error estimates made in the previous four sections are directly applicable in practice only when it is reasonable to assume that changes in normals over the last 30 yr are dominantly linear. The possibility that the shape may be otherwise or unstable is likely the source of some reluctance to adopt a new, albeit simple, approach like the hinge fit to replace the OCN. In fact, a comparison of performances in Table 3 (that are overstated for CPC/OCN) for the stronger trends ($\beta > 0.03$) observed commonly for U.S. surface temperatures and precipitation over the last 30 yr suggest that the hinge will produce substantial gains even for trends linear to just first order.

Examples of two U.S. climate divisions (and there are many) for which β well exceeds 0.03 for JFM mean temperature but the climate normal since 1975 is not clearly tracking in a straight line are shown in Fig. 8. In both cases the mean temperatures seem to have leveled off (at much higher levels than pre-1980) over the last 20 yr so that the CPC/OCN gives lower estimates of the 2005 normals than does the hinge. For desert California and the Sierra Nevada (Fig. 8a; $\beta = 0.06$) the transition appears gradual from the mid-1970s, but for north central Montana (Fig. 8b; $\beta = 0.04$) it looks like it occurred more abruptly in the late 1970s.

The differences in the character of these time series and that for western Colorado (Fig. 5; $\beta = 0.06$) may be partially or mostly a consequence of climate noise. Western Colorado does not have much of a winter ENSO signal, but the other two locations do and the respective ENSO impacts are nonlinear (Livezey et al. 1997; Montroy et al. 1998). The possibility that the differences are also the result of real differences in local (or regional) processes also governing recent climate change cannot be discounted, however. In any case, climate models universally predict warming to continue.

Perhaps a better model for time-dependent U.S. seasonal temperature normals is a parabolic hinge, in which the data can dictate a flatter (semicubical parabola) or steeper (cubical parabola) growth after the mid-1970s. Such a model has all the advantages of the hinge—smooth piecewise continuous fits to a stationary climate followed by a changing one, utilizing all the data and allowing straightforward extrapolation—but

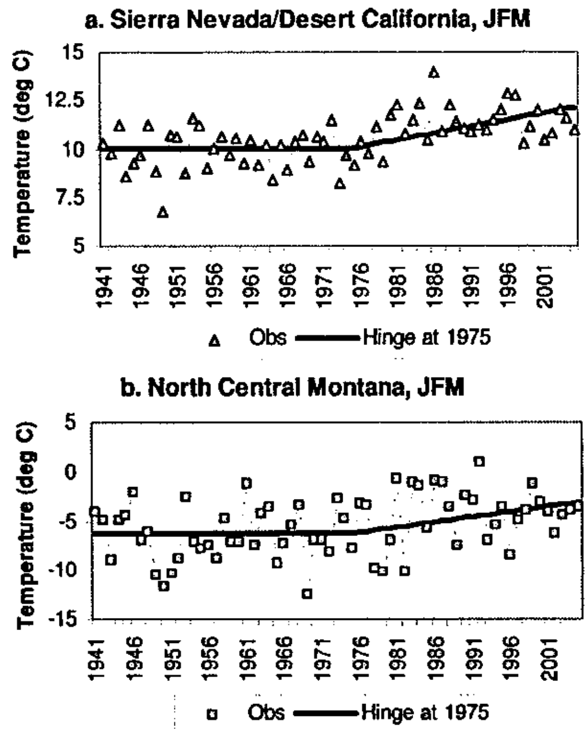

FIG. 8. January–March mean temperatures for (a) the Sierra Nevada and desert California and (b) north-central Montana, and the ordinary least squares hinge fits to the two time series.

with the flexibility to accommodate departures from linear growth. On the other hand, it is unclear whether there is a physical basis for this choice. Nevertheless, this and other techniques, including adaptive techniques that can accommodate changes in slopes, need to be explored more thoroughly.

More sophisticated low-pass filters than moving averages (i.e., OCN) are frequently used to smooth climate time series. These approaches are purely statistical and do not explicitly address normals as time-dependent expected values, either through use of collateral observational and dynamic model information or time series models to represent the physical processes. A good discussion of these methods that emphasizes the problem of fitting a climate time series near its current endpoint is by Mann (2004). In that paper, the best representations of the recent behavior of the Northern Hemisphere annual mean temperature are produced with use of different versions of the so-called minimum-roughness boundary constraint.

From the perspective of the discussions here and in section 3b, the resulting trends in Mann (2004) are likely modest overestimates of the rate of recent increases in temperature normals. This is a consequence of cooling trends between approximately 1950 and the mid-1970s in the low-pass filtered series that are dominantly a consequence of the exceptionally cold 1970s in North America (cf. Solomon et al. 2007), which in turn is dominantly a result of an exceptionally cold eastern United States (mentioned earlier). There is little evidence that these downturns in the filtered time series are a consequence of other than "climate" noise. In this context it is also difficult to justify the use of these smoothed series for separating ENSO impacts from those of a changing climate, which is another reason (in addition to overestimation of recent trends) to prefer hinge fits.

To round out a comprehensive overview of estimation and extrapolation of climate normals, the progress in developing techniques for the analytical approximation of seasonal and diurnal dependencies of $Y(t)$ from available observations is summarized in appendix B.

4. Concluding remarks

It is clear from the analysis here that WMO-recommended 30-yr normals, even updated every 10 yr, are no longer generally useful for the design, planning, and decision-making purposes for which they were intended. They not only have little relevance to the future climate, but are more and more often unrepresentative of the current climate. This is a direct result of rapid changes in the global climate over approximately the last 30 yr that most climate scientists agree will continue well into the future. As a consequence, it is crucial that climate services enterprises move quickly to explore and implement new approaches and strategies for estimating and disseminating normals and other climate statistics.

We have demonstrated that simple empirical alternatives already exist that, with one simple condition, can not only consistently produce normals that are reasonably accurate representations of the current climate but also often justify extrapolation of the normals several years into the future. The condition is that recent underlying trends in the climate are approximately linear, or at least have a substantial linear component. We are confident that this condition is generally satisfied for the United States and Canada and for much of the rest of the world but acknowledge that there will be situations for which it is not. In this context, two approaches need to be highlighted:

1) Optimal climate normals are multiyear averages not fixed at 30 yr like WMO convention but adapted climate record by climate record based on easily estimated characteristics (linear trend and 1-yr residual autocorrelation) of the climate records. The OCN method implemented with flexible averaging periods only begins to fail for very strong underlying trends (between 0.5 and 1 standard deviation of the residual noise per decade) or for longer extrapolations with more moderate background trend (see Tables 2 and 3). Least squares linear trend fits to the period since the mid-1970s are viable alternatives to OCN when it is expected to fail (Fig. 4 and Table 3), but there is an even better alternative.
2) Hinge-fit normals are based on modeling their time dependence on the known temporal evolution of the large-scale climate and are implemented with generalized least squares. They exploit longer records to stabilize estimates of modern trends in local and regional climates; therefore, they not only outperform straight-line fits (Fig. 7) but even OCN for underlying trends as small as 0.3 standard deviation of the climate noise per decade (Table 3).

Given these results, we make three recommendations:

1) The WMO and national climate services should formally address a new policy for changing climate normals and other climate statistics, using the results here as a starting point.
2) NOAA's Climate Office, NCDC, and CPC should cooperatively initiate an ongoing program to develop and implement improved estimates and forecasts of official U.S. normals.
3) As a first step, NCDC and CPC should work together to exploit quickly the potential improvements to their respective products demonstrated here. To be specific, the simple hybrid system described in section 3b that combines the advantages of both the OCN and the hinge fit should be implemented in regular operations as soon as possible to produce new experimental products.

As new work on climate normals and their use for forecasts of climate variability and change moves forward, climate analysts need to be cognizant of two points emphasized in sections 3a and 3b:

1) Linear or other trends should never be fit to a whole time series or a segment arbitrarily; the functional form of the trend should be based on examination of the time series and, to the extent possible, additional considerations.
2) Any assessment of the historical impacts of ENSO and their use in risk analysis or prediction *must* take into account climate change and, to the extent possible, separate its effects.

The additional considerations mentioned in the first point immediately above can include results or insight from state-of-the-art climate models. Until now a discussion of the role such models can play in the work and programs we are recommending above has been deferred. There are two potential uses for models that best track the large-scale climate and can replicate at least to first order the variability associated with ENSO and other important modes of interannual variability (i.e., the climate noise). Both uses depend on the fact that the time dependence of climate normals is "known" reasonably well (at least for some parameters, places, and seasons) if the ensemble of model runs is large enough and the runs do not span time scales on which long-term drift associated with, for example, the thermohaline circulation becomes important. In these instances a qualifying model can be used 1) to gain insight about the functional form of regional and subregional trends and 2) as a tool to test competing empirical methods for estimating and projecting these trends. Of course, efforts continue to improve the ability of climate models to replicate the climate comprehensively at smaller spatial and shorter temporal scales. We look forward to when these models can do this credibly and be directly exploited for computing climate normals and other climate statistics.

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APPENDIX A

U.S. Megadivision 3-Month Mean Temperature and Precipitation Trends

Maps of hinge-based trends (section 3b) of 3-month mean temperature and precipitation for 102 U.S. climate megadivisions (formed from the original 344) are shown in Figs. A1 and A2.

Climate-division data are often used at CPC (Barnston et al. 2000; Schneider et al. 2005) instead of station data because of the noise reduction inherent in aggregating nearby stations that strongly covary on intraseasonal to interannual time scales. The original 344 divisions are aggregated to 102 megadivisions mostly through combination of small adjacent divisions in the eastern half of the United States. Western divisions are essentially identical in both datasets. The reduction to 102 was originally done to approximate an equal-area representation for the United States, which is especially desirable for principal component–based studies; however, the additional aggregation provides further noise reduction for the adjacent, strongly covarying eastern divisions. Numerous studies reaffirm that the 102-division setup is more than sufficient to capture the spatial degrees of freedom in the coherent variability of U.S. seasonal mean temperature and precipitation. Megadivision normals are simple arithmetic averages of those for the divisions that compose them.

Data spanning from 1941 (1931) to 2005 with the hinge at 1975 are used to fit the temperature (precipitation) data at each division for each 3-month period. Combined with Fig. 1, Figs. A1 and A2 span the whole year. Based on arguments presented in sections 3a and 3b, we believe the trends displayed here more accurately represent modern U.S. climate change than any previously published.

On each temperature trend map the first color generally does not represent an important trend. The same is true for precipitation except for season/locations that are arid/semiarid. The overall bias for all maps is dominantly warming and significantly toward increasing precipitation. Note for temperature trends (Figs. 1a and A1) that 1) the Southwest has warming trends in every season; 2) west of the high plains the country has significant and consistent warming trends winter through summer (Figs. 1a and A1a,b), 3) trends are dominantly weak and inconsistent east of the high plains in summer (Fig. A1b) and autumn (Fig. A1c), and the Southeast has mostly a weak cooling trend in the spring (Fig. A1a); and 4) the wintertime trend map (Fig. 1a) is remarkable, reflecting almost-continent-wide warming (the exception is Maritime Canada, not shown).

For precipitation trends (Figs. 1b and A2), only the Northwest (autumn/winter; Figs. 1b and A2a,c) and Texas (spring/summer; Figs. A2b,c) have large areas of negative precipitation trends in more than one season and these are mostly small. Note that much of the crop-producing United States outside Texas and some of its surroundings has positive precipitation trends in the growing season (Figs. A2b,c). There is no indication in these results of a trend toward more drought nationwide. Among several area/seasons where trends are upward, the south-central region in the autumn (Fig. 1b) stands out as the most notable.

APPENDIX B

Annual and Diurnal Cycles in Climatic Trends

The annual cycle in seasonal mean normals is often much larger than typical day-to-day weather-related fluctuations. In addition to season-to-season variations in multiyear averages, climatic trends also display seasonality. The general approach to approximation of seasonal cycles in climatic trends has been formulated

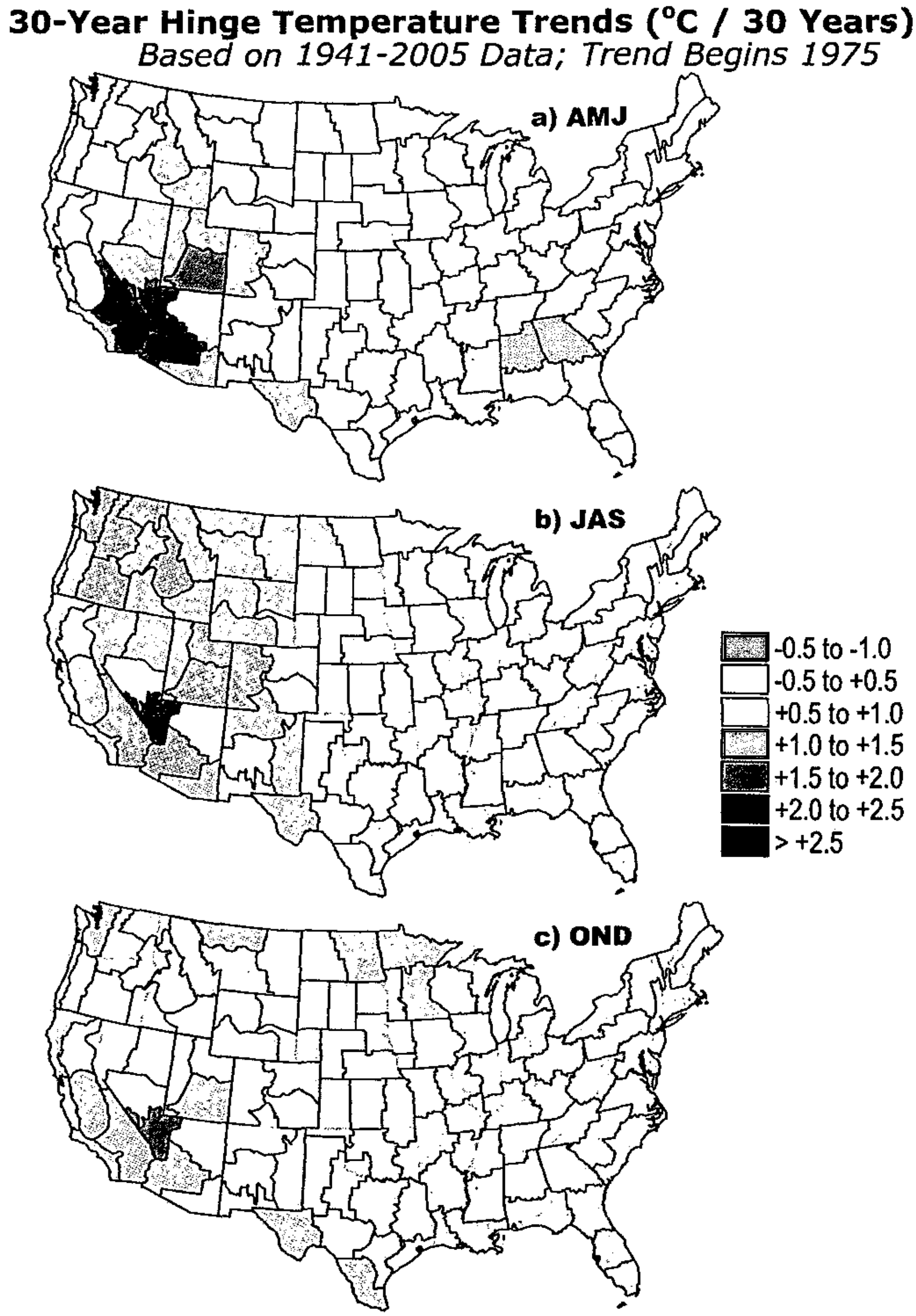

Fig. A1. As in Fig. 1, but for 3-month mean temperature for (a) April–June, (b) July–September, and (c) October–November.

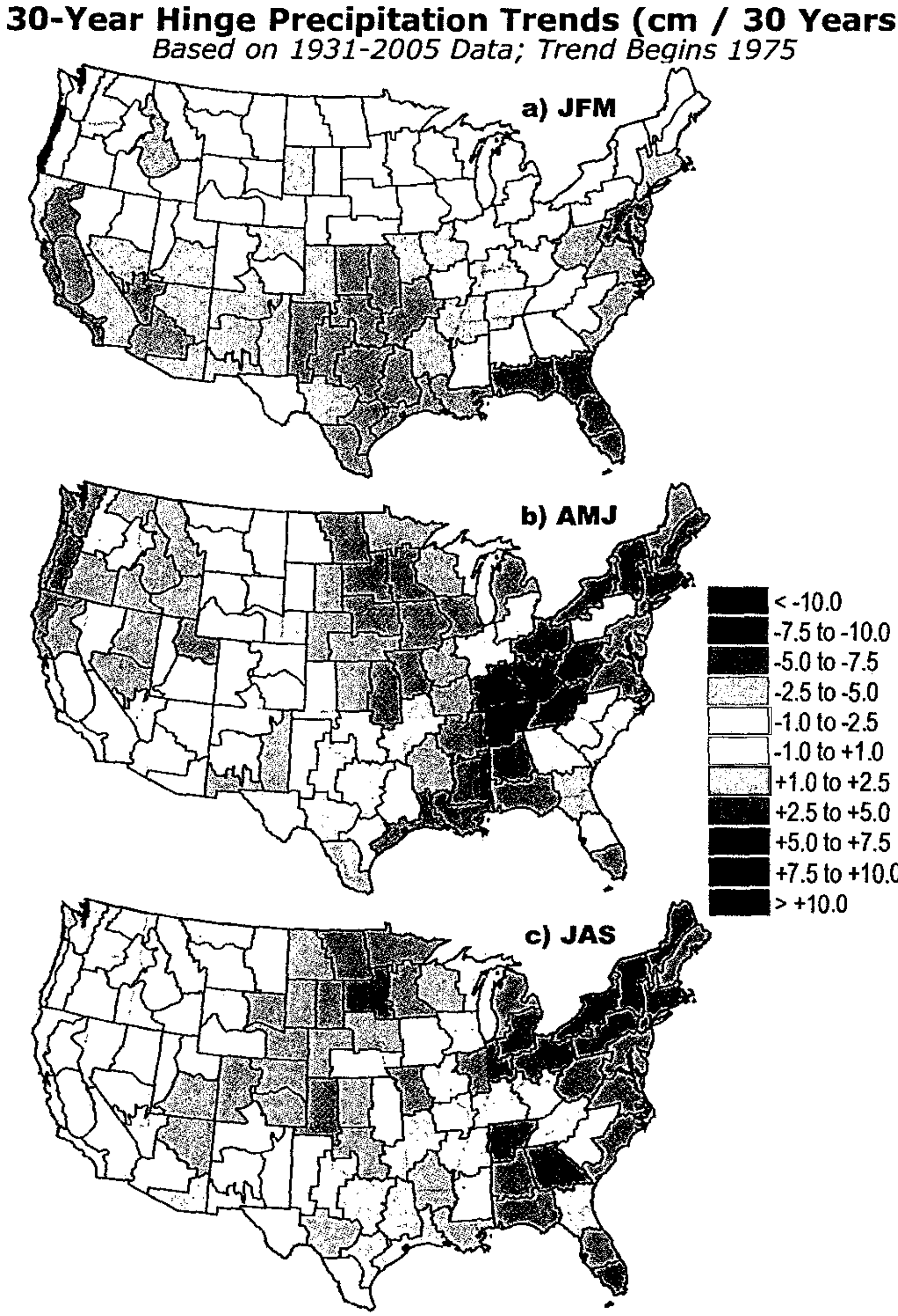

FIG. A2. As in Fig. 1, but for 3-month mean precipitation for (a) January–March, (b) April–June, and (c) July–September.

by Vinnikov et al. (2002b). The main idea is that instead of $Y(t) = a + bt + ct^2 + \cdots$ with constants a, b, c, and so on, the polynomial approximation of the expected value $Y(t)$ is written

$$Y(t) = A(t) + B(t)t + C(t)t^2 + \cdots, \qquad \text{(B1)}$$

where $A(t) = A(t + T)$, $B(t) = B(t + T)$, $C(t) = C(t + T)$, and so on, are unknown periodic functions with period $T = 1$ yr. Vinnikov et al. (2002a,b) and Cavalieri et al. (2003) used a linear trend assumption and a limited number of Fourier harmonics of the annual period to approximate $A(t)$ and $B(t)$ for daily observed hemispheric sea ice extents and surface air temperatures.

Different techniques need to be used for variables with seasonal cycles that cannot be approximated properly with a small number of harmonics of the annual cycle. Such techniques can be based, for example, on piecewise least squares approximation of periodic functions $A(t)$, $B(t)$, and so on, by algebraic polynomials in the vicinity of each specific phase of a seasonal cycle.

In addition to the seasonal cycle there is a diurnal cycle in most climatic records, and there can be diurnal cycles in trends as well. In such a case, the generalized coefficient functions $A(t)$, $B(t)$, and so on, in (B1) consist of short-time diurnal variations with a fundamental period of 1 day superimposed on the longer-period annual cycle (Vinnikov and Grody 2003; Vinnikov et al. 2004, 2006). Such processes are well known as amplitude-modulated signals in radio physics.

This approach has been tested using multidecadal time series of hourly observations of surface air temperature at selected meteorological stations (Vinnikov et al. 2004). In addition, application of this new technique to satellite microwave monitoring of mean tropospheric temperatures made it possible to resolve a contradiction between satellite and surface observations of contemporary global warming trends (Vinnikov and Grody 2003; Vinnikov et al. 2006).

A limited number of Fourier harmonics is often also not sufficient to obtain an accurate approximation of the shape of diurnal cycles. As before, other classes of periodic functions can be found or constructed to improve approximations of $Y(t)$. In this instance, estimation of $Y(t)$ can be based on patchwise least squares approximation of periodic functions $A(t)$, $B(t)$, and so on, by two-dimensional algebraic polynomials in the vicinity of each specific phase of seasonal and diurnal cycles.

These techniques can be used also for approximation and evaluation of climatic trends and cycles in variance, lag, and cross correlation and in higher moments of the statistical distribution of climatic variables, in the same way that the least squares technique is used for approximation of trends in expected value. Estimates of $Y(t)$ can be utilized to compute residuals $y'(t)$ for each t. Then, using the same technique for the variables $y'(t)^2$, $y'(t)^3$, $y'(t)^4$, $y'(t)y'(t \text{ lag})$, $x'(t)y'(t)$, and so on, we can evaluate trends in variance and other moments of the statistical distribution of the variables $y(t)$ and any other variable $x(t)$. This idea has been recently formulated and applied to study trends in variability of selected climatic variables (Vinnikov and Robock 2002; Vinnikov et al. 2002a). However, no statistically significant trends were found in twentieth-century variability of the large-scale climatic indices that were analyzed.

Studying seasonal (and diurnal) cycles in variances and lag correlations is necessary if we want to use the generalized least squares technique instead of the ordinary one to estimate unknown parameters in (B1). Taking into account the covariance matrix of observed data, the generalized least squares technique provides a more accurate estimate of $Y(t)$ and a much better estimate of its accuracy (Vinnikov et al. 2006).

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Warming shifts gardeners' maps

By Elizabeth Weise, USA TODAY

Every gardener is familiar with the multicolor U.S. map of climate zones on the back of seed packets. It's the Department of Agriculture's indicator of whether a flower, bush or tree will survive the winters in a given region.

It's also 18 years old. A growing number of meteorologists and horticulturists say that because of the warming climate, the 1990 map doesn't reflect a trend that home gardeners have noticed for more than a decade: a gradual shift northward of growing zones for many plants.

The map doesn't show, for example, that the Southern magnolia, once limited largely to growing zones ranging from Florida to Virginia, now can thrive as far north as Pennsylvania. Or that kiwis, long hardy only as far north as Oklahoma, now might give fruit in St. Louis.

Such shifts have put the USDA's map at the center of a new chapter in the debate over how government should respond to climate changes that were described in a report last year by a United Nations-backed panel of scientists. The panel said there was "unequivocal" evidence of global warming fueled by carbon dioxide emissions, which have created an excess of the greenhouse gases that warm the Earth.

GOING GREEN: Test your eco-understanding with interactive graphics and find the latest environmental news

Climate change is reshaping how people garden. Across the agricultural industry, the issue is driving a dispute over climate maps that involves economics, politics and meteorological standards.

At nurseries across the nation, it has become common knowledge that the government's climate map is out of date. And yet the nursery industry, which had $16.9 billion in wholesale sales in 2006, has joined the USDA in taking a conservative approach to changing the map.

A big reason: money.

Nurseries commonly offer money-back guarantees on plants. Analysts say many in the industry are worried that adjusting the climate maps would encourage customers in cooler areas to increasingly buy tender, warm-weather plants unlikely to survive a cold snap.

And growers are worried that their losses won't be sufficiently covered by the Federal Crop Insurance Corp.'s Nursery Crop Insurance Program, which covers them for losses caused by weather-related events such as flooding. If growing zones move north because of warming there is still a possibility of cold snaps, and it's unclear exactly how insurance programs would deal with that risk.

The USA's climate zone map designates 11 major belts for growing plants, from the relative cold of Zone 1 — which includes Fairbanks, Alaska — to midrange temperatures of Zone 6 (which includes parts of Missouri, Tennessee and southern Pennsylvania) to the heat of Zones 10 and 11, which include Hawaii and southern Florida.

Changing zone boundaries to reflect warming could "have a significant impact on certain growers of certain plant species," says Dave Hall of National Crop Insurance Services, which represents insurance companies.

Economic factors shouldn't be placed above the science of climate change, says meteorologist Mark Kramer, who worked on the 1990 USDA map that remains in effect, as well as a proposed update in 2003 that showed a warming trend. The USDA rejected the 2003 map.

"If nature changes, industry should change with it," Kramer says. "If the weather changes, we shouldn't operate with zones and systems that aren't appropriate."

AVERAGES DEPEND ON DECADE

Plant-hardiness zones are based on a single number: the average of the lowest temperature recorded each winter for a period of time.

But that number depends upon what time period you're averaging. The 1970s was a cold decade, the 1980s was warmer, and the 1990s was one of the warmest on record.

So an average that includes the 1970s would make most areas look colder than an average based only on the 1990s.

That's where the controversy comes in. During the past two decades, three versions of the map that shows 11 major plant-hardiness zones have been prepared for the Department of Agriculture: the 1990 official version that remains in effect; the 2003 update the agency rejected that reflected a warming trend; and a new map that the USDA says is coming within a year.

Zones for each map shift, depending on the years of weather data upon which it is based.

To explain the confusion, USA TODAY used weather data from the National Climatic Data Center and calculated average annual minimum temperatures for 11 U.S. cities. That average changes a lot depending on the time span used in the calculation.

For example, the average annual low temperature for Columbia, S.C., based on the 1990 map (1974-1986) is 10 degrees. The 2003 draft map (1986-2002) is 16 degrees. The new map is based on data from 1976-2005. Using data from those years, the average is 13.5 degrees.

(For data on the other 10 cities, visit usatoday.com).

By Elizabeth Weise and Anthony DeBarros, USA TODAY

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What polls, activists reveal

USDA officials reject suggestions that the agency's resistance to changing the 1990 map reflects a reluctance to acknowledge the potential impact of climate change. They say the agency wants its next map to reflect a 30-year period that gives a fuller picture of the world's climate than the 16-year examination Kramer conducted for his rejected map.

"The majority of the scientific community thought 30 years of credible data made the most sense," says Kim Kaplan of the USDA's Agricultural Research Service.

Kramer and other skeptics say the USDA's tactic will lead to an analysis that mutes the effect of warming trends during the past decade.

The agency's delay in releasing an updated map has led another group to release its own climate map. In 2006, the Arbor Day Foundation put out a map based on data from 1991 to 2005 that shows a significant northward movement of warm zones for plants and crops.

"Everyone's entitled to their opinion," Arbor Day Foundation's Woodrow Nelson says of the USDA map. But he says his group, which provides low-cost trees, was seeing trends that it wanted reflected in a map for growers.

"With the millions of trees that we're putting into the hands of people across the country, the most recent data available is important. Data from 30, 40 years ago is really kind of irrelevant in the life of a young tree."

Avid gardener Toni Riley, who lives on a small farm in Hopkinsville, Ky., with her family and a cadre of dogs, cats, sheep, goats and a horse, also values the most up-to-date information. "What I plant depends on the weather," she says. "I personally am very concerned about climate change."

The data debate

There's no denying the warming trend and its increasing impact on plants, says David Ellis, editor of *The American Gardener*, published by the American Horticultural Society. "We don't really need a dramatic new map to show us this."

Perhaps, but there's been a fair amount of drama as plant, weather and agriculture specialists have wrangled over the climate map.

The debate is rooted in the type of analytical divide that separates scientists who disagree over whether enough data are available to show whether the Earth's warming trend of the past two decades is a long-term problem.

Weather patterns tend to run in cycles, usually 10 to 15 years. Among meteorologists, 30 years is widely considered to be a good indicator of the overall climate.

"It's been the custom in climatology for a long time to represent long-term averages or 'normals' by a 30-year average," says George Taylor, a state climatologist for Oregon. "When you have a 15-year period, you can get some squirrelly numbers."

The United Nations World Meteorological Organization standard for assessing the climate is 30 years, says Kelly Redmond, a climatologist with the Desert Research Institute in Reno. But "that was before issues of climate change seriously put themselves on the plate."

The recent pace of climate change — the U.N. Intergovernmental Panel on Climate Change says 11 of the 12 warmest years since 1850 came between 1995 and 2006 — means gardeners must be more flexible, Redmond says.

"We could be heading into a time where the temperature is always above 'normal,' " he says. "If a plant has a short lifetime, what are the odds of that plant being killed by a climate event? If it's a tree or something that you want to live longer, you're probably a little more conservative (in choosing your plants) because even if the (climate) zones are slowly migrating, that doesn't mean there won't be cold spells."

Crop growers want the safest possible estimate of how cold it might get because they don't want to lose plants. Because the

TIME PERIOD AFFECTS TEMPERATURE ANALYSIS

Depending on the years studied, the average annual minimum temperature of a region on which hardiness-zone maps are based can vary up to 6 degrees. These are the average annual minimum temperatures for three time periods, reflecting the direction of three different hardiness-zone maps:

	1974-1986(a)	1986-2002(b)	1976-2005(c)
Columbia, S.C.	10.0	16.0	13.5
Redmond, Ore.	-6.3	-0.6	-3.1
Idaho Falls	-15.2	-11.0	-12.4
Abilene, Texas	8.9	13.1	11.5
Dayton, Ohio	-9.6	-5.9	-7.9
Paducah, Ky.	-0.3	3.1	1.0

Glasgow, Mont.	-28.4	-27.1	-28.5
Tucson	24.5	25.2	25.4
Valentine, Neb.	-23.9	-23.4	-23.7
Sacramento	26.7	26.5	26.8
Caribou, Maine	-24.4	-24.9	-23.7

a) 1990 USDA hardiness-zone map

b) 2003 draft map rejected by the USDA and posted online by American Horticultural Society

c) Proposed updated USDA map

Source: National Climatic Data Center; USA TODAY analysis by Anthony DeBarros

USDA's constituency is farmers and growers, the agency decided to use a 30-year standard for data in putting together its new climate map, which could be released as soon as the fall, according to Kaplan.

"The majority of the scientific community thought 30 years of credible data made the most sense," she says. "The conspiracy theorists think the reason we went to 30 years was that it would dilute the effects of global warming. That's flat-out wrong. No one has ever sat on the plant-hardiness map because they wanted to deny global warming."

Even so, meteorologists and horticulturists say it is the USDA's duty to more accurately show how the climate affects plants and crops. They include those who devised the 1990 map: Kramer and Marc Cathey, then-president of the American Horticultural Society.

A question of accuracy

The 1990 map was based on just 13 years of weather data, Kramer says. He and Cathey had hoped to do a new map every 10 years to reflect shifts in the weather.

Kramer's 2003 map rejected by the USDA was based on data from 1986 to 2002 and showed a significant march northward of boundaries for warm-weather plants. For example, plants that for decades had frozen and died in Nebraska suddenly were doing just fine.

Kramer isn't convinced the decades of data the USDA insists on having provide the most accurate picture of the climate that gardeners face now.

"If I was going to the garden center today, I'd want to have the most current, updated information. I don't want to know what happened 50 years ago."

Some see the changing horticultural landscape as a good thing.

"There are nurserymen who are excited about the new market" for plants in the northern half of the United States, Ellis says. "There are the ones who see ... it as a marketing opportunity."

That helps explain why, without fanfare, the horticultural society posted on its website the 2003 climate map rejected by USDA and dubbed it "The American Horticultural Society *draft* USDA plant hardiness zone map."

The map to be released soon by the USDA is being prepared by the Prism group at Oregon State University, known for doing sophisticated climate modeling. The 1990 map designated growing zones as small as counties; the new one will narrow the focus to square miles.

So what's a gardener supposed to do in the meantime?

Sometimes, says the National Arboretum's Scott Aker, the best thing to do is talk to someone who's really down in your local dirt. Nurseries and public gardens are good resources, he says.

Joan Pond Laisney of Carlsbad, Calif., consulted a garden-center expert before planting her tree-shaded garden. "We researched what grows well out here and what will live long-term," she says.

Aker says your neighbors can be a big help, too.

"Nobody is more familiar with soil and weather conditions in your yard than the person down the street with the beautiful garden," he says, "because usually what went into making that garden was a lot of mistakes and dead plants."

Contributing: Anthony DeBarros

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Redefining 'normal'

NCDC experiments with new climate standards

by Bob Henson

Climate was once viewed as being more or less stationary, with 30-year averages serving as an accepted guide to the future. Yet most of the United States has warmed significantly since the 1970s. And despite some intense regional droughts, large parts of the nation are considerably wetter on average than they were three decades ago.

To help its user groups get a better handle on such trends, NOAA's National Climatic Data Center (NCDC) is incorporating climate trends into an experimental set of averages that will evolve more quickly than the normals now cited on weathercasts and elsewhere.

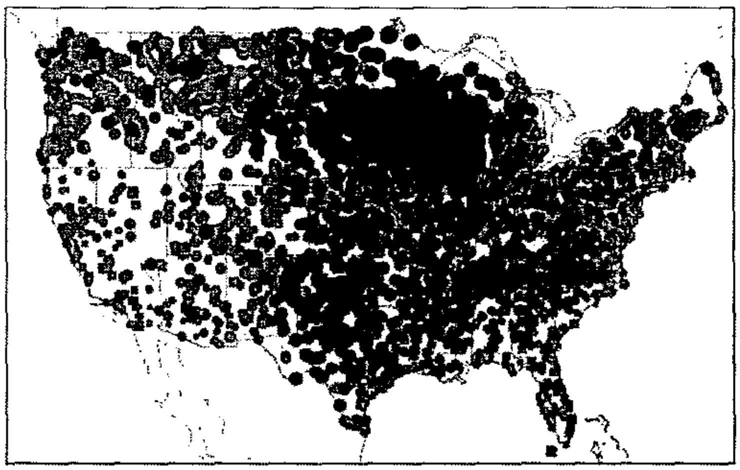
"The official normals are now 23 years out of date," says NCDC's Anthony Arguez, who heads up the project. Under protocols recommended by the World Meteorological Organization, normals are calculated every decade for 30-year periods. Today's normals, which are based on data from 1971–2000 and thus centered on 1985–86, lag behind the climate itself, especially for particular U.S. regions and seasons (see graphic). And the next update, which will span 1981–2010, won't be available until at least 2011.

This spring NCDC will unveil three alternative sets of U.S. climatic normals:

- *Moving averages*. These will be similar to the current method's results, except the period of record will roll ahead each year. For example, users will be able to access normal values for the period 1979–2008 later this year, 1980–2009 next year, and so on. According to Arguez, the underlying data that go into the averages were processed by NCDC with new adjustments to reduce bias and enhance homogeneity.
- *Optimal climate normals* (OCN). The OCN technique has been used for many years at NOAA's Climate Prediction Center (CPC) to help keep long-range seasonal forecasts in tune with climate change. Using time series statistics, an "optimal" averaging period is determined. Generally, strong trends (either positive or negative) will lead to shorter averaging periods, and vice versa. For its seasonal predictions, CPC used averaging periods of 15 years for precipitation and 10 years for temperature. For its OCN climate products,

NCDC will tailor the averaging periods for each station and each month of the year, based on local trends.

- *Hinge-fit normals.* As noted in many studies, the mid-1970s marked a turning point as the globe and nation entered a period of pronounced warming. The hinge-fit technique accommodates this shift by splitting a long-term time series into two line segments—a stationary part (pre-1976) and a linear trend component (1976 onwards).



This graphic compares the difference in mean monthly minimum temperatures for Januarys in 2001–07 compared to 1971–2000. It shows that parts of the U.S. Midwest are now experiencing midwinter mornings more than 5°C (9°F) warmer than the average readings calculated in the traditional way. Circles (squares) indicated warmer (cooler) conditions, and symbols not colored gray are statistically significant at 90% confidence, based on a bootstrapped t-test. (Image courtesy Anthony Arguez, NOAA/NCDC.)

The need for improved normals was stressed in a 2007 paper in the *Journal of Applied Meteorology and Climatology* by CPC's Robert Livezey and colleagues. (Livezey retired in 2008, but is actively advising Arguez on the normals.) The paper examined the above alternatives and proposed the OCN technique now being adopted. Traditional normals "are no longer generally useful for the design, planning, and decision-making purposes for which they were intended," wrote Livezey. "It is crucial that climate services enterprises move quickly to explore and implement new approaches and strategies for estimating and disseminating normals and other climate statistics."

There are downsides to the new approaches, says Arguez. For instance, the significance of a given anomaly (say, +1.5°C) will change from year to year in the moving-average datasets. And a frequently updated set of normals, if presented without proper context, could make it harder for the public to discern that the climate itself is changing. However, users such as large utilities should find that the new normals help them gauge the actual climate more effectively. "We focused from the beginning on the energy industry," says Arguez. "That's where we get a lot of feedback."

The new products will be formally introduced this spring via a webcast to be co-hosted by the American Meteorological Society's Energy Committee and NCDC. The webcast will be advertised on NCDC's What's New page. Users will still be able to access the familiar 1971–2000 averages. For more details, contact Arguez.

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