7-1-2015

Climate controls on air quality in the Northeastern U.S.: An examination of summertime ozone statistics during 1993-2012

Evan M. Oswald
University Corporation for Atmospheric Research

Lesley Ann Dupigny-Giroux
University of Vermont

Eric M. Leibensperger
State University of New York at Plattsburgh

Rich Poirot
Vermont Department of Environmental Conservation

Jeff Merrell
Vermont Department of Environmental Conservation

Recommended Citation

Oswald EM, Dupigny-Giroux LA, Leibensperger EM, Poirot R, Merrell J. Climate controls on air quality in the Northeastern US: An examination of summertime ozone statistics during 1993–2012. Atmospheric Environment. 2015 Jul 1;112:278-88.

NOAA Local Climate Analysis Tool (LCAT)

Data, Methods, and Usability

BY MARINA TIMOFEYEVA-LIVEZEY, FIONA HORSFALL, ANNETTE HOLLINGSHEAD, JENNA MEYERS, AND LESLEY-ANN DUPIGNY-GIROUX

With frequent references in the media to climate change, the public often requests information on climate and its impacts. Local field offices of the National Oceanic and Atmospheric Administration (NOAA)'s National Weather Service (NWS) encounter numerous climate-related questions, such as those related to expected weather in upcoming seasons, the causes of drought and the relationship to climate change, as well as the impacts of El Niño on snowpack. Many industries such as energy, agriculture, agribusiness, transportation, and natural resource management integrate climate information into their planning and operating procedures on a regular basis. In addition, significant changes in national and international policies regulating actions of industrial enterprises require the use of scientifically sound climate information. In the United States, one such driver is the June 2013 President's Climate Action Plan (www.whitehouse.gov/sites/default/files/image/president27sclimateactionplan.pdf), which states that "[t]he Administration will continue to lead in advancing the science of climate measurement and adaptation and the development of tools for climate-relevant decision making by focusing on increasing the availability, accessibility, and utility of relevant scientific tools and information."

AFFILIATIONS: TIMOFEYEVA-LIVEZEY, HORSFALL, AND MEYERS—Climate Services Division, Office of Climate, Water, and Weather Services/NWS/NOAA, Silver Spring, Maryland; HOLLINGSHEAD—Innovim, Honolulu, Hawaii; DUPIGNY-GIROUX—Department of Geography, University of Vermont, Burlington, Vermont

CORRESPONDING AUTHOR: Dr. Marina M. Timofeyeva, W/OS4, Climate Services, Rm. 13344, SSMC2, 1325 East West Highway, Silver Spring, MD 20910

E-mail: Marina.Timofeyeva@noaa.gov

DOI:10.1175/BAMS-D-13-00187.1

NWS has responded to this increased demand for local climate information by developing the Local Climate Analysis Tool (LCAT). The tool provides rapid responses to climate questions that historically required an extensive data search, research on appropriate analysis techniques, and complex graphics packages. LCAT offers easy and efficient access to scientifically sound analytical capabilities and trusted climate data. Results obtained from LCAT provide relevant climate information to local technical users, decision makers, and educators that will help build a healthy nation and create resilient communities.

Phase 1 of LCAT was launched into NWS operations on 1 July 2013 (http://nws.weather.gov/lcat/). This paper describes the building blocks of LCAT, including data, analytical capabilities, and applications, and outlines a vision for future capabilities.

LCAT DATA AND METHODOLOGY. To ensure that LCAT responds to the articulated needs for local climate studies, a team of representatives from the NWS field offices routinely collects and ranks needs for capabilities to be incorporated into LCAT. The team also helps to design the LCAT user interface and provides training on the tool's features, methods, and usability. The development process brings together scientific expertise from the NOAA internal and external climate community into Science Advisory Teams (SATs) who recommend methods and datasets for each LCAT analysis section. The LCAT development and evolution cycle is an ongoing and iterative effort: the field representative team continually addresses new requirements, the SATs identify and recommend data and methods, and the development team creates code and conducts case studies to test the tool. Additional testing of new functions is done prior to implementation through a group of NWS users, who provide feedback to the development team, which in turn addresses the comments or asks for additional guidance from the SATs.

The SATs recommended the following regional and site-specific datasets for LCAT initial capabilities:

1) Station dataset of homogenized monthly and seasonal average, minimum, and maximum temperature and total precipitation data for more than 5,000 U.S. stations (Menne et al. 2009);
2) Climate Prediction Center (CPC)'s forecast region data of monthly and seasonal average temperature and total precipitation data for 102 CPC forecast regions (O'Lenic et al. 2008);
3) National Climatic Data Center (NCDC) climate division data of monthly and seasonal average, minimum, and maximum temperature, total precipitation, heating and cooling degree days, and several drought indices for 344 NCDC climate divisions (Guttman and Quayle 1996); and
4) Automated Climate Information System (ACIS) station data of monthly extremes for average, minimum, and maximum temperature, total precipitation, and snowfall (Hubbard et al. 2004).

Although the station data are available for the entire period of record (1895–present), the SATs recommended using the data from 1925 to the present as the most trusted data source because earlier data include too many inconsistencies. The regional data for forecast regions and climate divisions are available for the entire period of record (1895–present).

LCAT analysis components. The LCAT framework offers analyses of climate change impacts, climate variability impacts, and correlation. The analyses of climate change and climate variability impacts are generated on-the-fly and use the four datasets mentioned above. The correlation studies run directly through NOAA's Earth System Research Laboratory (ESRL), producing correlation plots of various signals using the NCDC Climate Division data (www.esrl.noaa.gov/psd/data/usclimdivs/) or NCEP-R1 Reanalysis data (www.esrl.noaa.gov/psd/data/correlation/).

Climate Change Impacts Analysis Techniques. The three trend techniques for analysis of local climate patterns and changes over long periods of time (Fig. 1) are the Hinge trend-fitting technique, the Optimal Climate Normal (OCN), and the Exponentially Weighted Moving Average (EWMA).

The hinge trend-fitting technique (Livezey et al. 2007) uses a linear piecewise regression model (1) that allows reduction of the sampling error in estimating the model parameters. The hinge linear model consists of a zero slope section and a positive/negative slope section. The least-squares regression technique fits the hinge trend line to the data. Numerous empirical studies and model simulations have concluded that 1975 is the most appropriate hinge anchor year (e.g., Livezey et al. 2007; Wilks and Livezey 2013).

$$Hinge_r = \begin{cases} a & for\ S \le r \le 1975 \\ a + bx_r & for\ 1975 < r \le R \end{cases} \tag{1}$$

where r is the year, S is the starting year, R is the last year, and $x_r = r{-}1975$ is the number of years after 1975. The coefficients a and b are the constants from least-squares regression over the entire data record:

$$a = \frac{\sum_S^R \text{data}_r}{N} \quad -b\frac{\sum_{1976}^R x_r}{N} \tag{1a}$$

$$b = \frac{\sum_{1976}^R x_r \sum_S^R y_r - N\sum_{1976}^R x_r y_r}{\left(\sum_{1976}^R x_r\right)^2 - N\sum_{1976}^R x_r^2} \tag{1b}$$

where data_r is the climate variable data for individual year of records, and $N{=}R{-}S{+}1$ is the total number of years.

The OCN (2) is a moving average of a time series over 10 years for temperature and 15 years for precipitation (Huang et al. 1996; Livezey et al. 2007). LCAT's OCN uses an 11-year moving average for temperature instead of 10 for the purpose of plotting the time series. Wilks and Livezey (2013) found that a 15-year averaging period for temperature may produce better results by yielding the smallest mean square error for predictions. LCAT allows averaging options for both time periods (11 and 15 years) for temperature. The OCN is plotted over the center year of each averaging period (Fig. 1).

$$OCN_r = \frac{\sum_{r-0.5\tau+0.5}^{r+0.5\tau-0.5} \text{data}_n}{\tau} \tag{2}$$

where τ is the averaging period and r is the center point of n, which is the vector of data consisting of τ members. The OCNs for the first and the last half averaging periods are assumed to be equal to the first and last OCN values, respectively.

The third trend-fitting option available in LCAT is the EWMA (www.itl.nist.gov/div898/handbook/pmc/section3/pmc324.htm) whose computation (3) includes weighting the most recent 15-year period more heavily than the OCN technique. The EWMA method plots the values at the center point of the 15-year period:

$$
EWMA_r = \begin{cases} \dfrac{\sum_1^{\tau} \text{data}_r}{\tau}; & for\ 1 \le r \le \tau \\ \left(1 - \dfrac{1}{(0.5 * \tau) + 0.5}\right) * \text{data}_r + \left(1 - \dfrac{1}{(0.5 * \tau) + 0.5}\right) * EWMA_{r-1}; & for\ r > \tau \end{cases} \tag{3}
$$

where τ is the EWMA period and r is the individual data record.

The OCN, hinge trend-fitting, and EWMA techniques allow for the analysis of different features of local climate change. The hinge method tracks the most current state of climate at a location. The OCN and EWMA methods track changes in climate normals defined as a time series average of recent time periods such as 10/11, 15, or 30 years (www.nws.noaa.gov/directives/sym/pd01010004curr.pdf). To analyze climate change in terms of the current climate and climate normals together, the SAT recommends the use of an ensemble approach or the average of all selected trends (Fig. 1). The ensemble computations also include the minimum and maximum values for all chosen trends to analyze variability in the ensemble spread and assess the uncertainty inherent in the data and methods: the bigger the spread, the greater the difference between the current climate and the climate normals.

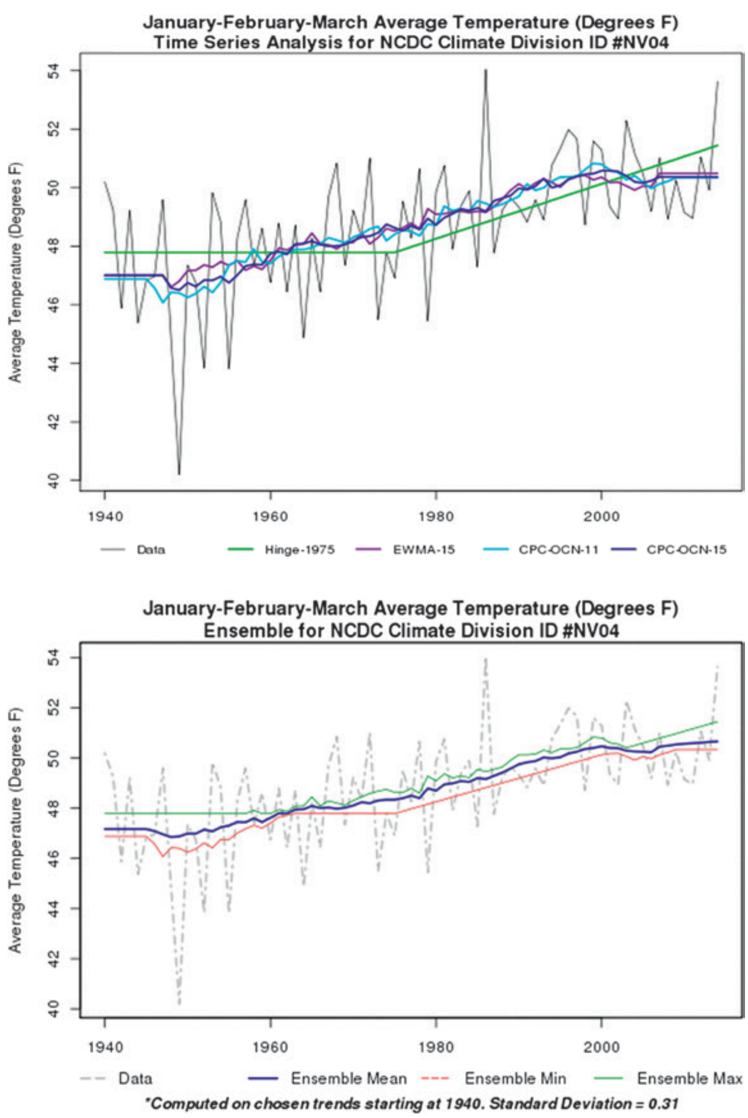

Fig. 1. Extreme Southern Nevada Climate Division (#NV04) average temperature during January/February/March from 1940 to 2014 for (top) all trend-fitting techniques (Hinge, EWMA, and OCN 11- & 15-year) and (bottom) ensemble (mean, maximum, and minimum) of all trend techniques.

LCAT computes the Rate of Change (ROC) of a climate variable over varying time frames ranging from annual to decadal to 30-year climatology. This rate of change represents the linear slope of a) the ensemble mean of selected trends, b) a single chosen trend, or c) the original time series.

A final option in the climate change impacts section is the generation of a climate time series that would be observed if the present climate record were preserved over the entire period of record. Users can perform the Detrend option (Fig. 2) and take the difference between each individual observation and the trend ordinates. These differences are then added to the very last year of the trend (4).

$$
\text{Detrend}_r = \text{Trend}_R + (\text{data}_r - \text{Trend}_r) \tag{4}
$$

where r is the individual data record and R is the last data record.

The approach assumes that variability in the climate data and climate change act independently from each other, thus their effects can be additive. Using the January/February/March average temperature at the

Extreme Southern Nevada Climate Division #NV04 for the purposes of illustration (Fig. 2), the hinge trend-fitting method was used to remove the trend from the original time series, with the departures being added back to the last year of the trend (4). The SAT recommends using a detrended time series whenever a user needs to analyze climate variability in the context of current climate change.

Information on uncertainty is critical for results obtained from analysis based on relatively short periods of instrumental records. Information on ROC confidence intervals can help LCAT users decide whether climate change at the local level is significant or not. Von Storch and Zwiers (1999) recommend assessing confidence intervals of the linear regression slope as:

$$\left(\mathrm{ROC}-\frac{t\sigma_E}{\sqrt{S_{xx}}},\mathrm{ROC}+\frac{t\sigma_E}{\sqrt{S_{xx}}}\right) \qquad (5)$$

where t is the quantile of the t-distribution with n–2 degree of freedom for specified confidence; σ_E is the standard deviation of the error in the regression fit; and S_{xx} is the sum of squared difference between the observed time series and its mean.

Table 1 displays the slope confidence intervals and the upper and lower limits of the slope computed for different methods for various confidence intervals for the Southern Nevada example (Fig. 2) average temperature during January/February/March from 1940 to 2014. The hinge estimates for the confidence limits are also approximated from Eq. (5). Hinge slope estimates use piecewise regression, which is not compliant with the Eq. (5) assumption of a simple linear regression. No standard statistical method is currently available to assess the exact confidence limits of the hinge slope. The authors are currently consulting with professional statisticians to identify a more appropriate method and will address this issue in future work.

Given that the time series are short (75 years) and the data error is relatively large, the range of slope values can vary from slightly negative to a large positive. The slope confidence limits, with qualifying error bars, do not provide usable information for assessing the significance of climate change impacts. Analyses of signal-to-noise ratio may better infer the ROC significance. Livezey et al. (2007) recommend using the ROC as a measure of the climate change signal and root-mean-square error (RMSE) as a measure of climate variability. A signal-to-noise ratio value of 0.05 or greater indicates a very steep slope. This ratio implies the climate change signal in 20 years

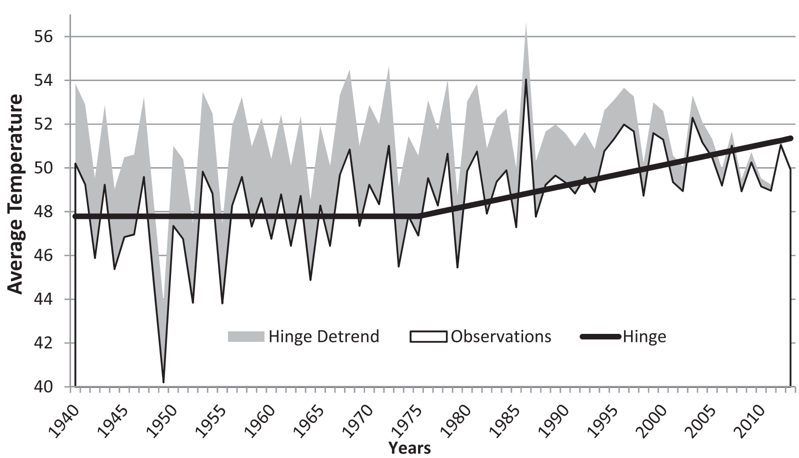

Fig. 2. Extreme Southern Nevada Climate Division (#NV04) average temperature during January/February/March from 1940 to 2014. Shaded area is the difference between detrended data and the original dataset.

Table 1. ROC confidence intervals computed for different trend methods and confidence intervals for Extreme Southern Nevada Climate Division #NV04 average temperature during January/February/March from 1940 to 2014.

Confidence Level	Hinge*ROC=0.094		OCN11 ROC=0.07		OCN15 ROC=0.071		EWMA ROC=0.064	
	Lower*	Upper*	Lower	Upper	Lower	Upper	Lower	Upper
75%	0.036	0.152	0.003	0.137	0.000	0.142	−0.008	0.136
90%	−0.016	0.204	−0.058	0.198	−0.065	0.207	−0.073	0.201
95%	−0.048	0.236	−0.095	0.235	−0.104	0.246	−0.112	0.240

* **Hinge slope confidence intervals use a method assuming simple linear regression; the actual estimates should be different for slope of piecewise regression.**

will be as large as the standard measure of the noise (climate variability); the signal will be twice as large as the noise in 40 years. The Southern Nevada example (Fig. 1) estimates the hinge signal-to-noise ratio as 0.057, indicating a significant rate of climate change in comparison to climate variability. The temperature normals (OCN and EWMA) also indicate swift changes, although not as rapid as the actual temperature records (hinge): signal-to-noise ratios are 0.038 for OCN-11, 0.038 for OCN-15, and 0.033 for EWMA. LCAT will include the information on the ROC error bar and the signal-to-noise ratio as resources permit.

Climate Variability Impacts Analysis Techniques. The LCAT climate variability impacts section provides composite analysis of relationships between climate variability drivers, such as the El Niño–Southern Oscillation (ENSO) and local climate variables.

CPC applies composite analysis operationally to their monthly climate outlooks (Huang et al. 1996; Xie et al. 2010). Composite analysis is a sampling technique that compares the probability distributions of an entire time series with the conditional probability of a certain local response observed during teleconnections, such as an ENSO event or the North Atlantic Oscillation (NAO). LCAT extends CPC's composite analysis methodology with two additional techniques.

The first is a test of composite significance to assess whether the relationship between the climate variability signal and local climate is random or represents a true signal. Significance testing allows the user to assess whether a statistically significant relationship exists between the climate variability signal (teleconnection) and the local climate (e.g., total precipitation, maximum or minimum temperatures). The test evaluates whether a unique outcome falls within a 10% tail of a hypergeometric distribution, which is used to describe all possible outcomes of a certain category of the local climate (Above, Near, Below Normal) to occur during a given phase of a teleconnection (Wolter et al. 1999).

The second technique is a trend adjustment to study climate variability in the context of the current state of climate change. The composite analysis with trend adjustment uses detrended time series (4) and univariate statistics of climatology to define categories and compute the probability of occurrence for a certain category during various phases of ENSO and other teleconnections.

Figure 3 shows composite analysis for Extreme Southern Nevada Climate Division #NV04 for January/February/March average temperature. The top bar graph represents the likelihood of each category in the time series. The temperature categories are defined by comparing all observations with those of the

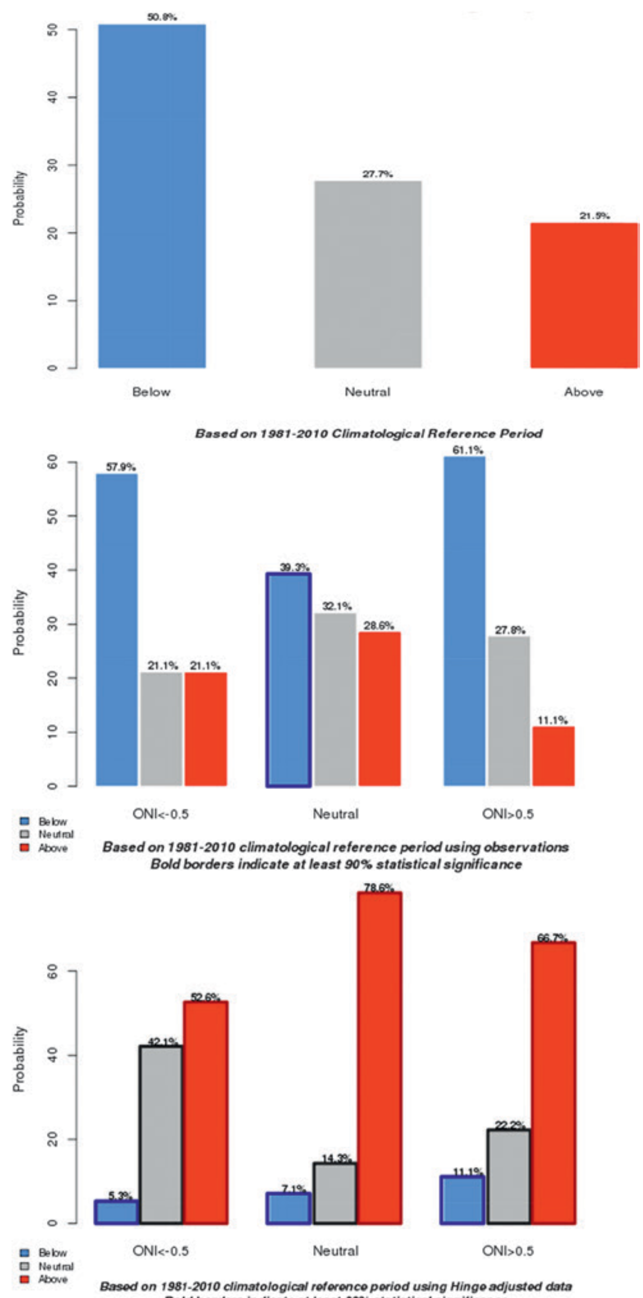

Fig. 3. Composite analysis for Extreme Southern Nevada Climate Division (#NV04) average temperature during January/February/March from 1950 to 2014. (top) Historical data distribution, (middle) composite analysis on raw data, and (bottom) composite analysis on data with the hinge trend adjustment. Bolded outline of the bars indicates statistically significant outcomes at 10% error level.

climatological period of 1981–2010. The data indicate the presence of a warming trend: there is a greater chance for below-normal temperatures observed during the period of analysis because the data have been compared with the relatively warm climatological reference period of 1981–2010. This means more data during the period from 1950–2014 were as cold as the coldest 10 years during the period of 1981–2010—or in other words, the temperatures were more often as cold or colder than the climatological threshold for the Below Normal category. Composite analysis on the raw data (middle bar graph) propagates the bias and provides misleading guidance as to what to expect during ENSO events for this local area. The adjustment to trend (bottom bar graph) indicates that the climate change signal is more dominant than the ENSO signals—regardless of ENSO phase—and that the likelihood for above-normal temperatures is greater than any other category.

The anomalies option in the LCAT climate variability analysis section provides the difference between the mean of a given variable (e.g., maximum temperature or total precipitation) during the selected phase of a teleconnection (e.g., La Niña) for the period of interest (1-month or 3-month season) from climatological normals. The boxplot analysis allows users to obtain historical distributions of a variable for the period of interest associated with different signal event phases. Additionally, LCAT time series analysis provides histograms, along with values of skewness and kurtosis in the output as a graphical representation of the distribution of the user-selected input data.

DEVELOPMENT OF LCAT CODE AND USER INTERFACE. The LCAT development team consists of a scientific programmer and a web designer who translates the SAT-recommended methods into the tool. Routine tests that include a step-by-step comparison between the LCAT code and an Excel method are conducted to insure correctness and accuracy of computations. These LCAT computation tests also include benchmarking output with peer-reviewed publications to insure consistency and accuracy of methods. Figure 4 demonstrates four case studies produced by

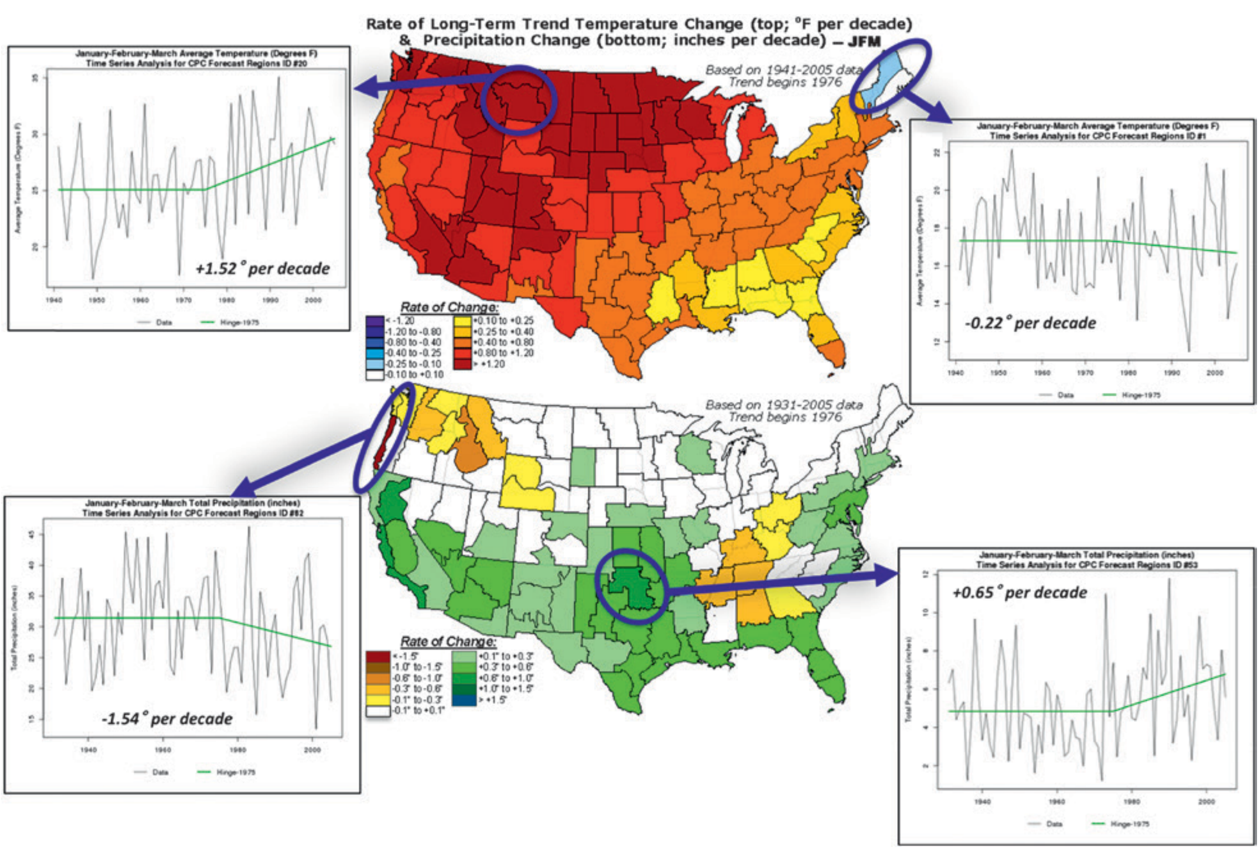

FIG. 4. Benchmark using peer-reviewed publication of rate of long-term temperature and precipitation change (Livezey et al. 2007) vs LCAT regional case studies.

LCAT using the same dataset and period, positively duplicating results published in Livezey et al. (2007). The SATs evaluate such case studies prior to approval and operational deployment.

LCAT output provides decimal precision using NOAA's conventional practice: the first-moment statistics (mean, median) contain 100th-decimal precision, while all higher-moment statistics such as standard deviation, skewness, and kurtosis contain 1,000th-decimal precision. The annual ROC 1,000th-decimal precision is important to more accurately describe the phenomenon. The decadal and climatological ROC decimal precision corresponds to the precision of the first-moment statistics. The primary motivation to report such decimal precision in LCAT statistics is to reduce computational errors due to different systems' rounding processes. Users may reduce decimal precision to fit their needs.

The NWS Internet Dissemination System (NIDS) hosts the LCAT operational system in a Linux environment using code scripted in Linux shell, Perl, R, and XML languages. The middleware code is integrated using Perl, PHP, JSON, jQuery, HTML, and XML languages.

The LCAT web interface generates analysis results on the fly in response to user-specified queries. LCAT forwards users' requests to the main Perl module that retrieves the requested dataset, runs the analysis, and returns the results in both graphical and textual format. Each query produces uniquely numbered output (which facilitates revisiting the same analysis at a later date) available for download in different formats (e.g., PDF, XML, CSV, etc.). The web-interface output includes scrollable graphics with corresponding statements, a variety of data statistics, metadata, a reiteration of the user's request, and an assortment of download options for all input and output. On-the-fly generation bypasses the need for either complex programming or the storage of large data volumes.

To insure consistency of the methodology across requests and datasets, LCAT code packages the algorithms for each analysis type into smaller, universal modules that can be accessed rapidly and applied to all datasets. Figure 5 demonstrates the general LCAT model. LCAT provides three mechanisms of user support: 1) Training modules located on the homepage "LEARN" tab that detail data, scientific methods, and potential applications, with special emphasis on LCAT's appropriate and inappropriate uses; 2) Interpretation statements that accompany each image and/or analysis type to promote correct translation and application of results; and 3) Help buttons located within

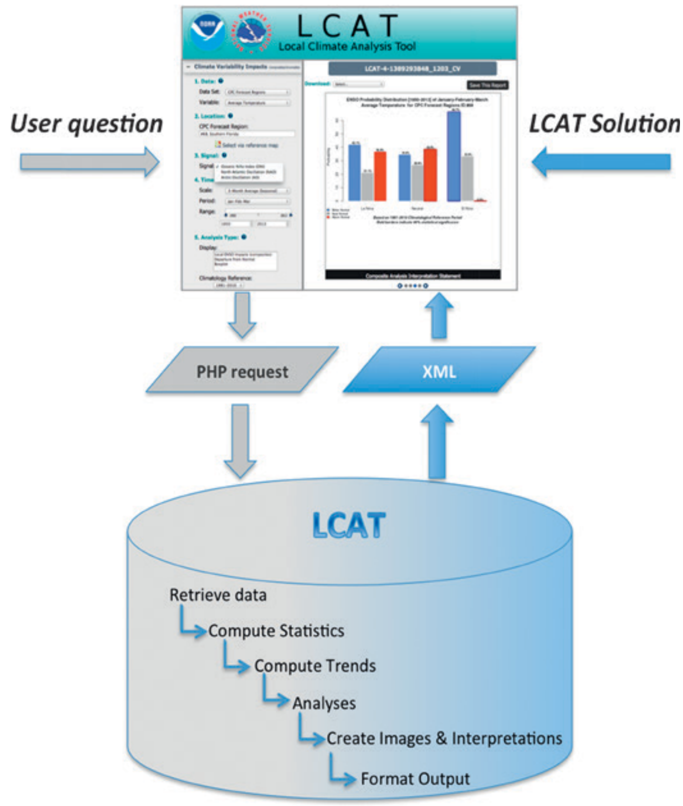

Fig. 5. The basic model of LCAT structure and flow.

every section that guide users through the tool. LCAT users are strongly encouraged to make use of the training modules and support tools to maximize proper application and comprehension of LCAT output.

LCAT APPLICATIONS. NWS climate services staff and technical decision makers are the main target audience for LCAT. Some examples of local impacts inquiries that NWS field offices receive on a regular basis are:

- How quickly has our minimum temperature risen over the last 50 years?
- Is our region getting wetter or drier?
- Will our precipitation change because we are heading into a given ENSO phase?

Changes in atmospheric dynamics during ENSO phases influence temperature and precipitation patterns across much of the United States. LCAT offers the ability to understand and analyze local climate change and variability of minimum and maximum temperatures, degree days, and drought. This capability provides a first step in developing new operational local climate products that can move beyond average temperature and total precipitation outlooks currently available in NWS. LCAT may also improve NWS climate services' effectiveness and delivery through rapid acquisition of data and analysis techniques.

LCAT's data access and analysis capabilities also serve state climatologists in their duty to provide research, communication, education, and outreach to diverse communities and stakeholders. Here too, user inquiries run the gamut from the comparison of a given storm or temperature extreme with its entire period of record to the rate of change in selected climate variables over the recent past vis-à-vis decades-to-century time scales. These queries are often intricately linked to decision-support strategies by town, county, or state agencies within a region. Examples of decision-support services include advanced preparedness and planning for extreme weather and water events that can be achieved through the understanding and effective use of information on weather–climate linkages. State climatologists and other climate service providers may use LCAT to assist stakeholders in gaining a more in-depth understanding of climate information applications. Their offices are also in the position to provide feedback on LCAT enhancements in terms of stakeholder-driven analyses. They may use the tool to add local value to climate outlooks, data analysis, decision-support guidance, climate assessments, and education. For example, state climatologists may use LCAT to periodically report current local rate of change of various climate parameters to stakeholders. This may include incorporating LCAT ENSO impact output results as an additional climate product on their websites. The use of LCAT as well as other NOAA climate tools in state climate offices adds a level of consistency between their climate services and NOAA's and can minimize user confusion about climate information provided by different sources.

LCAT'S FUTURE. The principles behind the core of LCAT are what make the tool unique. The current capabilities reflect only a fraction of what is possible. While LCAT is meeting the immediate needs of NWS forecasters to provide rapid responses to customer requests, the tool can potentially incorporate varied datasets and analysis techniques.

Since LCAT's launch in July 2013, the tool's membership has exceeded 650 registered users as of September 2014, many of whom come from NOAA, other governmental offices, the media, academia, water resources management, energy facilities, and educators. Existing partnerships include collaborations with NCDC and the Northeast Regional Climate Center for the provision of data, and NOAA's CPC and ESRL, the National Drought Mitigation Center, the Desert Research Institute, the American Association of State Climatologists, and the University of Arizona for advice on the scientific methods employed. The Department of Energy (DOE) is building the DOE Climate Analysis System (DCAS) that is based on LCAT principles and utilizes the LCAT codes and user interface. Common interests of the DOE and NWS have allowed accelerated development of the capability of LCAT to conduct local climate studies using future scenarios from the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report Models (AR5) (http://cmip-pcmdi.llnl.gov/cmip5/).

LCAT help buttons, training, and interpretation statements foster understanding of climate analysis. While these features are useful for technical users, nontechnical groups will benefit from improvement to this area. At the present time, the climate community continues to investigate methods for better communicating climate information. Future development of LCAT will leverage research advancements in communication techniques, thus enabling a greater understanding of local climate impacts presented by the tool.

The future of LCAT's development depends on engagement with the LCAT user community and the societal challenges supported by NOAA. Potential future collaborators include the Center for Disease Control and Prevention (CDC) and the National Institutes of Health (NIH) to develop climate applications for health-related decision making—for example, the analysis of regional and local mortality and morbidity resulting from extreme heat events or vector-borne diseases. LCAT provides valuable information on climate impacts for water and weather events that contributes to preparedness activities and advance planning in the face of our changing climate. This is a critical component to building a Weather-Ready Nation and supporting societal challenges outlined in the NOAA Next Generation Strategic Plan (www.ppi.noaa.gov/ngsp/).

ACKNOWLEDGMENTS. The authors express profound gratitude to Nicole McGavock, Barbara Mayes-Boustead, Clinton Rockey, Michael Churma, Kenneth Sperow, James Zdrojewski, and other NWS local-offices staff for providing field input during LCAT development. Our sincere appreciation goes to Tim McCalmant and other Orion staff who worked on developing the LCAT online interface, Robert Livezey for scientific advice throughout the work on this project, and Catherine Smith for help with the ESRL correlation tool. We are grateful to David Unger, Mike Halpert, Michelle L'Heureux, Anthony Arguez, Russell Vose, Bob Glahn, Wayne Higgins, Huug van den Dool, Mark Svoboda, Tim Brown, Muthuvel Chelliah, Jerry Bell, Derek Arndt, and other SAT members, who provided operational insight and scientific expertise. We are thankful for operational updates in NCDC homogenized datasets provided by Matthew Menne and Claude Williams. Support provided by Roger Pulwarty and David Herring helped to implement LCAT's drought and decision-support components The authors thank the NOAA Climate Program Office, CPC, NCDC, and Meteorological Development Laboratory for continuous support during LCAT development. We are also very thankful to the *BAMS* reviewers for valuable suggestions and critique that led to improvements in the paper.

FOR FURTHER READING

Global Historical Climatology Network Monthly (GHCNM) Version 3, 2014: [Available online at ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/v3/README.]

Guttman, N. B., and R. G. Quayle, 1996: A historical perspective of U.S. climate divisions. *Bull. Amer. Meteor. Soc.,* **77,** 293–303, doi:10.1175/1520-0477(1996)077<0293:AHPOUC>2.0.CO;2.

Huang, J., H. M. van den Dool, and A. G. Barnston, 1996: Long-lead seasonal temperature prediction using optimal climate normals. *J. Climate,* **9,** 809–817, doi:10.1175/1520-0442(1996)009<0809:LLSTPU>2.0.CO;2.

Hubbard, K. G., A. T. DeGaetano, and K. D. Robbins, 2004: SERVICES: A modern applied climate information system. *Bull. Amer. Meteor. Soc.,* **85,** 811–812, doi:10.1175/BAMS-85-6-811.

Livezey, R. E., K. Y. Vinnikov, M. M. Timofeyeva, R. Tinker, and H. M. van den Dool, 2007: Estimation and extrapolation of climate normals and climatic trends. *J. Appl. Meteor. Climatol.,* **46,** 1759–1776, doi:10.1175/2007JAMC1666.1.

Menne, M. J., C. N. Williams Jr., and R. S. Vose, 2009: The U.S. Historical Climatology Network monthly temperature data, version 2. *Bull. Amer. Meteor. Soc.,* **90,** 993–1007, doi:10.1175/2008BAMS2613.1.

NIST, 2013: NIST/SEMATECH e-Handbook of Statistical Methods. [Available online at www.itl.nist.gov/div898/handbook/pmc/section3/pmc324.htm.]

O'Lenic, E. A., D. A. Unger, M. S. Halpert, and K. S. Pelman, 2008: Developments in operational long-range prediction at CPC. *Wea. Forecasting,* **23,** 496–515, doi:10.1175/2007WAF2007042.1.

Von Storch, H., and F. W. Zwiers, 1999: *Statistical Analysis in Climate Research*. Cambridge University Press, 484 pp.

Wilks, D. S., 2013: Projecting "normals" in a nonstationary climate. *J. Appl. Meteor. Climatol.,* **52,** 289–302, doi:10.1175/JAMC-D-11-0267.1.

——, and R. E. Livezey, 2013: Performance of alternative "normals" for tracking climate changes, using homogenized and non-homogenized seasonal U.S. surface temperatures. *J. Appl. Meteor. Climatol.,* **52,** 1677–1687, doi:10.1175/JAMC-D-13-026.1.

Williams, C., M. Menne, and J. Lawrimore, 2012: Modifications to Pairwise Homogeneity Adjustment software to address coding errors and improve run-time efficiency. NCDC Technical Report NCDC No. GHCNM-12-02, 28 pp. [Available online at ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/v3/techreports/Technical%20Report%20NCDC%20No12-02-3.2.0-29Aug12.pdf.]

Wolter, K., R. M. Dole, and C. A. Smith, 1999: Short-term climate extremes over the continental United States and ENSO. Part I: Seasonal temperatures. *J. Climate,* **12,** 3255–3272, doi:10.1175/1520-0442(1999)012<3255:STCEOT>2.0.CO;2.

Xie, P., M. Chen, and W. Shi, 2010: CPC unified gauge-based analysis of global daily precipitation. *AMS 24th Conf. on Hydrology,* Atlanta, GA.