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ALTERNATIVE METRICS FOR MEASURING SURFACE HEATING TRENDS

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1. INTRODUCTION

Much interest is currently focused on inadvertent anthropogenic climate change (NRC, 2005), with surface temperature being one of the main metrics used to measure this change. Surface temperatures are generally estimated to have increased by 0.3 - 0.6 °C over the past century (IPCC, 2001). Surface temperature data are useful both for the length of record and since the surface is where humans conduct most of their daily activities (Hurrell et al., 2000). Air temperature by itself, however, may only be a partial metric of warming or cooling (Pielke et al., 2004). We propose using moist enthalpy, which accounts not only for surface air temperature but also for heat content associated with atmospheric moisture. The moist enthalpy at any given site is related to the site's surface energy balance, which in turn depends on microclimate. Moist enthalpy is given by

$$H = C_p T + Lq \,, \qquad (1)$$

where C_p is the specific heat of air at constant pressure, T is the measured air temperature, L is the latent heat of vaporization, and q is the specific humidity. Specific humidity can be calculated from measurements of relative humidity, dewpoint temperature or wet bulb temperature (Davey, 2005).

2. DATA AND METHODS

Moist enthalpy can be represented by effective temperature $T_E = H/C_p$. We look at 1982-1997 trends in T and T_E for surface sites in the eastern United States (Figure 1),

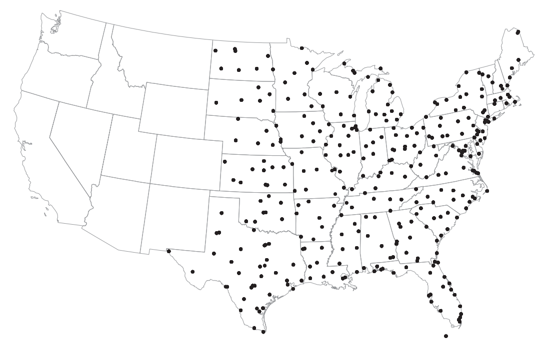

Figure 1. Locations of surface observation sites

using the International Surface Weather Observations (ISWO) dataset (NCDC, 1998). The ISWO dataset has undergone extensive quality control and consists of observations taken every three hours. No homogeneity adjustments had been made to this data, however, so an attempt was made to correct for documented ASOS (Automated Surface Observing System) and AWOS (Automated Weather Observing System) transitions. For each site, annual averages of T and TE were computed for the year before and the year after the transition date. These annual averages were then differenced to compute the correction factor, which was applied to the original data. Other discontinuities are likely to exist but were not addressable in this work since data histories are not yet summarized efficiently. This additional, very substantial work should be a high priority for follow-on studies.

Monthly means of temperature (T), dewpoint temperature (T_d), station elevation (z), and sea level pressure (p_o) were computed for each ISWO station. The actual monthly mean pressure was estimated as

$$p = p_0 e^{-z/h} \,, \qquad (2)$$

where z is station elevation and h is the scale height (h = 8 km). Once p is known, the monthly mean specific humidity (q) and the mean equivalent temperature (T_E) were calculated as in Davey (2005).

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We then constructed 1982-1997 time series of each variable for each month. The 1982-1997 trend was estimated using a basic linear regression model

$$y = \beta x + \varepsilon \,, \qquad (3)$$

where β is the trend and ε is the error. The ratio of the trend estimate, b, to the standard error of the trend estimate, SE(b), given by

$$\tau = b / SE(b) \,, \qquad (4)$$

is distributed as Student's t and was used to determine whether or not an estimated trend b is significantly different from zero. This was done by comparing τ to a specified significance level α.

With climate variables, autocorrelation must be accounted for. If it is assumed that the observation errors are independent of each other and normally distributed around zero, this will tend to exaggerate the overall error. The error term for each observation, ε_t, must be replaced with the term

$$v_t = \varepsilon_t - \sum_{i=1}^{m} \varphi_i v_{t-i} \,, \qquad (5)$$

which accounts for all autocorrelations up to lag m. The vector $\varphi = (\varphi_1,\ldots,\varphi_m)$ is the vector of autoregressive parameters while $v = (v_1,\ldots,v_m)$ is the error vector.

The Yule-Walker (YW) method (Gallant and Goebel, 1976) is a commonly used estimation method used for the autoregressive error model and has been used here. This method alternates between estimating the actual trend value, β, using generalized least squares (GLS), and estimating the autoregressive parameters φ applied to the sample autocorrelation function, using the YW equations

$$R\varphi_{est} = -r \,. \qquad (6)$$

The current estimation of the autoregressive parameters is given by φ_{est}, $r = (r_1,\ldots,r_m)$ is the vector of sample autocorrelations covering lags 1 through m, and R is the Toeplitz matrix, the i,jth element of which is $r_{|i-j|}$. Once the best estimate for the actual trend β is obtained, a t-ratio (4) is then computed for the trend estimate to determine whether or not this estimate is significantly different from zero.

Trend estimates were computed for only those time series having at least 10 available data points (years) and the trend estimates accounted for autocorrelations covering up to four years (i.e. lag-4). This choice for the maximum lag interval was intended to remove most interannual influences. Comparisons of the T and T_E trend estimates were done annually (i.e. including all observations throughout the year) and seasonally (i.e. January-March, April-June, etc.) for the entire surface dataset. Similar comparisons were done for the subsets of the T and T_E trends that were significant at the 90%, 95% and 99% significance levels. Finally, the variability of both T and T_E trends as a function of land use/land cover was examined, using land-cover classes (Table 1) in the National Land Cover Dataset (Vogelmann et al. 2001).

Land Cover Class	Description
1	Deciduous Forest
2	Evergreen Forest
3	Mixed Forest
4	Grassland
5	Shrubland
6	Row Crops
7	Small Grains
8	Pasture/Hay
9	Urban
10	Water
11	Other - ice/snow, bare surfaces, wetlands, orchards

Table 1. Land cover classes from the National Land Cover Dataset (NLCD – Vogelmann et al., 2001).

There are a wide variety of microclimates encountered at surface weather stations around the United States (Davey and Pielke, 2005). The land cover of a surface observation site is a primary factor in describing that site's microclimate (Pielke et al., 2000; Kalnay and Cai, 2003). The predominant land-cover category for each station was determined by finding which land cover has the largest proportion of cells in a 3-km X 3-km area (9 grid cells, or 9 km^2) centered on the station of interest.

3. TEMPERATURE VS. EQUIVALENT TEMPERATURE

3.1. *Annual and seasonal patterns*

Annually, when the trend estimates of all stations are averaged together, the T trends are cooler than the T_E trends. The difference between the T and T_E trends is significant at >99%. This relationship continues when one only averages over those trends which are significantly different from zero.

Seasonally, the averaged trends for T_E show more warming than T from the winter through the summer, while they show less warming than T trends during the fall. When the comparisons are narrowed to look only at those individual trends that are significantly different from zero at a specified significance level, these differences between the T and T_E trends remain significant at over 99%.

3.2. *Land use/land cover influences*

On an annual basis, the difference between the T and T_E trends is insignificant for forests. T_E trends are significantly cooler for agricultural sites, while they are significantly warmer for grasslands, shrublands, urban areas, and water areas. The corresponding annually-averaged trends in specific humidity indicate that for those sites where q has decreased with time, the T_E trends are cooler than the T trends. The opposite is true for those land-cover classes where q has increased over time.

During the winter months, the only land-cover classes showing differences between the T_E and T trends that are significant above 90% are the shrubland sites, the urban sites, and the water sites. The sample sizes for the shrubland and water averages are small, however. The spring differences between the averaged T_E and T trends are significant (T_E trends significantly more warming than T trends) for shrubland sites, sites with small-grain agriculture, and water sites; yet all of these averages suffer from small sample sizes. For the summer months, grasslands and shrublands generally indicate that the trends for T_E are warmer than the T trends. The cooling trends for T_E are significantly cooler than the T trends during the fall months.

4. DISCUSSION AND CONCLUSIONS

To completely understand surface warming/cooling trends, we must better understand the surface energy budget and its role in determining surface heating trends. Based on existing problems with documentation of surface station microclimates and the complex land-atmosphere interactions that influence the surface energy budgets at these sites, temperature by itself is not sufficient for monitoring heating trends. We have attempted to show that, for the monitoring of surface trends, moist enthalpy, or equivalent temperature, is a more appropriate metric than air temperature. Equivalent temperature directly accounts not only for dry air temperature (sensible heating) trends but also trends in heating driven by changes of surface and atmospheric moisture. Moist heating effects are implicitly included in air temperature, but air temperature, by itself, is not total heat content.

The overall results from this study indicate that annually, the equivalent temperature trends are warmer than the temperature trends. This is also observed in the spring and summer months, during which vegetation transpiration is at a maximum. As Pielke et al. (2004) have shown, outside of the growing season, equivalent temperature and temperature values are very similar to each other. It is during the growing season that the differences between the two quantities become most apparent. Equivalent temperature does, in fact, appear to be more sensitive than air temperature alone to annual variations in vegetation and other land surface characteristics. This finding also is generally borne out in the seasonal variations in temperature and equivalent temperature heating trends. Equivalent temperatures are useful for diagnosing spatial variations in heating trends as a function of land cover and may help resolve reported discrepancies between tropospheric and surface heating trends (Hansen et al., 1995; Hurrell and Trenberth, 1996; Bengtsson et al., 1999). As the science community continues exploring alternative ways to measuring heating trends and strive to further understand land-atmosphere interactions, particularly with respect to the surface energy budget, we can expect substantial improvements in our understanding of surface heating trends.

5. ACKNOWLEDGEMENTS

This work was supported under the NSF fellowship program entitled “Graduate Teaching Fellows in K-12 Education (GK-12)” (GKA01-0177), the Colorado Agricultural Experiment Station Project (CAES), the NSF GLOBE project (GEO-0222578), and the F/DOE/The University of Alabama in Huntsville's Utilization of Satellite Data for Climate Change Analysis" (DE-FG02-04ER 63841 through the University of Alabama at Huntsville). Dallas Staley and Odie Bliss performed their usual outstanding support for final editorial oversight of the paper. Chris E. Forest is acknowledged and thanked for his comments on the concept of moist enthalpy.

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