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Impacts of land use land cover on temperature trends over the continental United States: assessment using the North American Regional Reanalysis

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ABSTRACT: We investigate the sensitivity of surface temperature trends to land use land cover change (LULC) over the conterminous United States (CONUS) using the observation minus reanalysis (OMR) approach. We estimated the OMR trends for the 1979–2003 period from the US Historical Climate Network (USHCN), and the NCEP-NCAR North American Regional Reanalysis (NARR). We used a new mean square differences (MSDs)-based assessment for the comparisons between temperature anomalies from observations and interpolated reanalysis data. Trends of monthly mean temperature anomalies show a strong agreement, especially between adjusted USHCN and NARR ($r = 0.9$ on average) and demonstrate that NARR captures the climate variability at different time scales. OMR trend results suggest that, unlike findings from studies based on the global reanalysis (NCEP/NCAR reanalysis), NARR often has a larger warming trend than adjusted observations (on average, 0.28 and 0.27 °C/decade respectively).

OMR trends were found to be sensitive to land cover types. We analysed decadal OMR trends as a function of land types using the Advanced Very High Resolution Radiometer (AVHRR) and new National Land Cover Database (NLCD) 1992–2001 Retrofit Land Cover Change. The magnitude of OMR trends obtained from the NLDC is larger than the one derived from the 'static' AVHRR. Moreover, land use conversion often results in more warming than cooling.

Overall, our results confirm the robustness of the OMR method for detecting non-climatic changes at the station level, evaluating the impacts of adjustments performed on raw observations, and most importantly, providing a quantitative estimate of additional warming trends associated with LULC changes at local and regional scales. As most of the warming trends that we identify can be explained on the basis of LULC changes, we suggest that in addition to considering the greenhouse gases–driven radiative forcings, multi-decadal and longer climate models simulations must further include LULC changes.

KEY WORDS land use land cover change; reanalysis; temperature trends; observed minus reanalysis approach; US historical climate network

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1. Introduction

Temperature trends result from natural and anthropogenic factors; the latter (especially CO_2 resulting from human activities) has been mainly seen as the result of increasing concentrations of greenhouse gases (IPCC 2001; Trenberth *et al.*, 2007). Recent investigations have also shown that climate forcing from land use/land cover (LULC) change also significantly impacts temperature trends (e.g. Bonan, 1997; Gallo *et al.*, 1999; Chase *et al.*, 2000; Feddema *et al.*, 2005; Christy *et al.*, 2006, Roy *et al.*, 2007; Wichansky *et al.*, 2008). Some studies suggest that new metrics should be considered for characterizing climate changes (e.g. Pielke *et al.*, 2002a, 2004, 2007b; Joshi *et al.*, 2003; NRC, 2005; Williams *et al.*, 2005). Consequently, attention has been increasingly given to the impact of LULC change on climate. For example, it has been reported that land use changes due to agriculture lead to decreased surface temperatures (Mahmood *et al.*, 2006; Roy *et al.*, 2007; Lobell and Bonfils, 2008). LULC change can significantly influence climatological variables such as maximum, minimum and diurnal temperature range (Gallo *et al.*, 1996; Hale *et al.*, 2006, 2008). The effects of urbanization on climate trends have been analysed using classifications of meteorological stations as urban or rural based on population data (Karl *et al.*, 1988; Easterling *et al.*, 1997) or satellite measurements of night lights (Gallo *et al.*, 1999; Peterson *et al.*, 1999;

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Hansen *et al.*, 2001). Various studies of urban heat island have determined land surface/temperature impacts of different magnitudes (Kukla *et al.*, 1986; IPCC, 2001; Peterson, 2003). Other non-climatic factors have been found to have significant impacts on temperature trends: e.g. corrections due to changes in the times of observation, type of equipment and station location (Karl *et al.*, 1986; Quayle *et al.*, 1991; Hansen *et al.*, 2001; Pielke *et al.*, 2002b; Vose *et al.*, 2003).

The increasing evidence that some non-radiative forcings such as LULC change may also be major factors contributing to climate change has prompted the National Research Council (NRC, 2005) to recommend the broadening of the climate change issue to include LULC processes as an important climate forcing.

Recent studies have used the 'observation minus reanalysis' (OMR) method to estimate the impact of land use changes by computing the difference between the trends of surface temperature observations and reanalysis datasets (Kalnay and Cai, 2003; Zhou *et al.*, 2004; Frauenfeld *et al.*, 2005; Lim *et al.*, 2005, 2008; Kalnay *et al.*, 2006, Pielke *et al.*, 2007b; Nuñez *et al.*, 2008). The OMR method is effective because some reanalyses do not assimilate surface temperature over land and therefore are not directly sensitive to near surface properties. Moreover, this method separates land surface effects from human-caused and natural climate variability caused by changes in atmospheric circulation, as these changes are included in both observations and reanalysis (Kalnay *et al.*, 2008).

Thus, the impact of land surface can be estimated by comparing trends observed by surface stations with surface temperatures derived from the reanalysis data. Likewise, the reanalysis can be used to detect non-climatic biases that are introduced by changes in observation practices and station locations (Kalnay *et al.*, 2006, Pielke *et al.*, 2007a, 2007b).

So far, the primary reanalysis datasets for the aforementioned OMR studies have been the NCEP/NCAR, NCEP/DOE and the European Center for Medium range Weather Forecasting (ECMWF) 40-year (ERA40) reanalyses. The OMR signals in the ERA-40 are similar but weaker than those in the NCEP reanalyses because the ERA-40 made some use of surface temperature observations over land to initialize soil moisture and temperature (Lim *et al.*, 2005). Building on the NRC (2005) recommendations and the IGBP integrated land ecosystem – atmosphere processes study (iLEAPS) framework, the objective of this study is to improve our understanding of LULC change impacts on temperature trends at local and regional scales using relatively new and high resolution datasets. The analysis is twofold: (1) we compare the trends of US historical climate network (USHCN) adjusted and unadjusted temperatures with the ones derived from the higher resolution North American Regional Reanalysis (NARR) as a method for detecting a signature of land surface properties on temperature trends. Like the NCEP global reanalysis, NARR does not use surface temperature observations (Mesinger *et al.*, 2006) and therefore is a good reanalysis to estimate the impacts of surface processes using OMR. (2) We investigate the sensitivity of surface temperature to LULC changes over the conterminous United States by analyzing OMR trends with respect to two datasets: the land cover classification derived from the advanced very high resolution radiometer (AVHRR) and the new national land cover database (NLCD) 1992/2001 Retrofit Land Cover Change.

Section 2 reviews the data and methods. Section 3 presents the results of (1) OMR trends over the United States and (2) the sensitivity of surface temperatures to land cover types. The summary and conclusions are presented in section 4.

2. Data and methods

The surface observation data used in this study consist of monthly mean temperatures for 1979–2003 from the USHCN (Easterling *et al.*, 1996) obtained from http://cdiac.ornl.gov/epubs/ndp/ushcn/monthly.html. We focus on raw as well as adjusted temperatures. However, even though most of the USHCN stations have very long periods of record, the raw data is not continuous and, in some instances, the amount of missing data makes it difficult to perform accurate trend analyses. For this reason, the use of the raw data was limited (15 stations for individual comparisons with the reanalysis), as compared to that of the adjusted data (586 stations used for the analysis at national level). We also used reanalysis data from NARR obtained at http://nomads.ncdc.noaa.gov. NARR has been developed as a major improvement upon the earlier NCEP/NCAR and NCEP/DOE in both resolution (32-km grid increments) and accuracy (Mesinger *et al.*, 2006). It has taken advantage of the use of a regional model (the Eta Model) and advances in modelling and data assimilation. With NARR, very substantial improvements in the accuracy of temperatures and winds compared to those of NNR have been achieved throughout the troposphere (Mesinger *et al.*, 2006). Also, as compared to the NCEP/NCAR and NCEP/DOE, NARR has a higher temporal resolution (3-h time intervals). Thus, not only are analysis and first-guess fields available at shorter time intervals but also a considerable fraction of the data are being assimilated at more frequent times (Mesinger *et al.*, 2006).

The set of stations used for a comparison with the reanalysis at individual site level span both rural and urban areas in the eastern United States. The choice was based on record length (all stations have less than 8% of missing data) and on information (station quality, geographical location, urban-rural type) provided by local climatologists and National Weather Service personnel.

As in Kalnay and Cai (2003), we applied the OMR method by linearly interpolating the NARR gridded temperatures to individual station sites and then removing the monthly mean annual cycle from both interpolated reanalysis and observations. The resulting time series

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and their trends were compared at different time scales (monthly, seasonal and long term) by means of the linear trends of 10-year running windows, which smoothes out the short-term fluctuations and random variations and highlights long-term trends. As a result of this procedure, the trends were presented for the period December 1983–January 1998.

For the comparisons between temperature anomalies from unadjusted (U) or adjusted (A) observations and interpolated reanalysis data (N), we employed the mean squared differences (MSDs),

$$\mathrm{MSD}_1 = E\left[(U - N)^2\right] \text{ and}$$
$$\mathrm{MSD}_2 = E\left[(A - N)^2\right] \tag{1}$$

where E[] stands for the mathematical expectation, or the mean, or the ensemble average. The common practice is to use the correlations instead, which is less appropriate. First, correlation is only one among several factors contributing to MSD (e.g. Kobayashi and Salam, 2000); second, interpreting the correlation coefficient is complicated as various features of the data under study may strongly affect its magnitude (Wilcox, 2003).

In our analysis, a positive difference

$$d = \mathrm{MSD}_1 - \mathrm{MSD}_2 \tag{2}$$

would indicate that the adjustments are consistent with the reanalysis, and the larger the d, the better the adjustments perform in reducing the differences between NARR and the observed anomalies.

The difference d is estimated from the data by

$$\hat{d} = \frac{1}{n}\sum_{i=1}^{n}(u_i - n_i)^2 - \frac{1}{n}\sum_{i=1}^{n}(a_i - n_i)^2, \tag{3}$$

where n is the number of observations for a station, u_i, a_i and n_i are the unadjusted, adjusted and reanalysis values respectively. The accuracy of such estimation was characterized by 90% bootstrap confidence intervals for unknown true values of d (for details see Appendix).

To investigate the spatial patterns of temperature trends, we generated a gridded USHCN dataset of the adjusted temperatures from 586 USHCN stations that are well distributed nationwide, and then regridded the resulting surface to the NARR resolution.[1] (An R script asks for a user-defined resolution (here, the NARR one), and interpolates observed values of the 586 stations to gridpoints using the simple Kriging method with the exponential variogram model.) Spatial patterns of OMR were derived from the new grids by using the Spline interpolation method (Spline with tension) with ArcGIS Spatial Analyst. Given the substantial amount of missing data, converting the raw USHCN observations into gridded information resulted in inaccurate values and, therefore, we did not include the raw data in this segment of the analysis. All trends were computed using a simple linear regression and their degree of significance was assessed using the related P-values.

We examined the sensitivity of surface temperature to land cover types by using two land cover datasets:

- the land cover classification derived from AVHRR (Hansen *et al.*, 2000). The 1-km grid increment data originates from the Global Land Cover Facility (University of Maryland) and consists of 14 land cover types for North America (12 represented over the CONUS). The dataset has a length of record of 14 years (1981–1994), providing the ability to test the stability of classification algorithms (Hansen *et al.*, 2000), and the related OMR analysis was performed over the same period.
- the NLCD 1992/2001 Retrofit Land Cover Change (Homer *et al.*, 2007), obtained from the multi-resolution landcharacteristics (MRLC) website. This new US Geological Survey dataset was created using 76 standard mapping zones (65 over the CONUS) regrouped in 15 larger zonal areas (14 over the CONUS) and has a 30-m resolution. The dataset was generated using a decision tree classification of Landsat imagery from 1992 and 2001. The resulting product consisted of unchanged pixels between the two dates and changed pixels that are labelled with a 'from–to' land cover change value. In this study, out of 87 classes for the whole dataset, only 25 are considered: 5 unchanged LULC types (urban, barren, forest, grassland/shrubland and agriculture) and 20 classes that depict conversion types.

Using both datasets conveys much more information on land use/cover types and allows an analysis based on both static and dynamic datasets.

ArcGIS, which integrated the different data sources, was used to (1) create a subset of the AVHRR dataset for the CONUS; (2) compute OMR values from interpolated observations and reanalysis temperature trends (for the LULC change analysis, OMR values were computed over the same period as the period of acquisition of the dataset: 1992–2001); (3) convert the resulting OMR surface to gridpoints using the Spatial Analyst 'Sample' tool and (4) convert the gridded LULC datasets into polygon shapefiles representing land cover types. OMR gridpoints that belong to each LULC type were selected and exported as individual tables and summary statistics were derived for each type.

While the gridded analysis was done for all the USHCN sites, we chose 15 different CONUS stations for more detailed assessments that included reviewing station history files and related reports to document the local changes. As initially shown in Kalnay and Cai (2003) and verified in several follow-up studies, the analysis of a subset of stations provides robust results and conclusions regarding the processes and the impact of LULC on the temperature trends (Lim *et al.*, 2008).

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3. Results

3.1. Observation, reanalysis and OMR trends

The comparison, on a station-by-station basis, of temperature anomalies from surface station observations and interpolated reanalysis data (e.g. Figure 1(a)), shows a good agreement in the inter-annual variability of surface observations and NARR (e.g. correlation coefficient of adjusted USHCN *vs* NARR for Orangeburg: 0.93). This agreement confirms findings from previous studies, which show that both NCEP/NCAR and NARR satisfactorily capture the observed intra-seasonal and inter-annual fluctuations (Kalnay and Cai, 2003; Kalnay *et al*., 2006; Pielke *et al*., 2007a). Furthermore, the combined use of observations and reanalysis can yield additional information that is related to station environment and observation practices. For example, Orangeburg, SC, which is located in a wooded residential area within the city limits with no significant obstruction within 200 feet, experienced a number of changes: moved 0.25 miles SW from its previous location (November 1984), new temperature equipment (August 1992), altered sensor elevation (February 1994) and time of observation (from 24 : 00 to 7 : 00 effective January 1996). The differences in the USHCN observations and reanalysis in Figure 1(a) can be attributed to these documented changes that took place at the station and were not recorded by NARR. As a result, the 10-year running window trends (Figure 1(b)) show substantial differences between raw and analysed temperatures throughout most of the study period and highlights the stronger sensitivity of observed temperature trends to surface properties. Therefore, the comparison between surface observations and NARR is efficient in detecting LULC changes that took place at the vicinity of stations or changes related to observation practices.

The adjustments made at some stations considerably reduced the differences between NARR and observed anomalies. For example, the MSD method reveals that the impact of adjustments are particularly noticeable in Orangeburg (South Carolina), Portage (Wisconsin), Conception and Rolla University (Missouri), as attested by their larger value of d, which represents the difference between MSDs (Figure 2). The MSD results show that 14 out of 15 of the stations investigated in this study exhibit statistically significant differences. Of these, 11 stations show positive differences (Table I).

Table II shows the decadal temperature trends for the 15 stations, and their OMR (trend differences) for the 1979–2003 period. From one station to another, the trends vary considerably. However, fewer variations occur in the NARR trends (smaller standard deviation: 0.16 °C), as compared to the raw observed trends (0.22 °C) and, to a lesser extent, the adjusted trends (0.17 °C). Such patterns were also observed with the

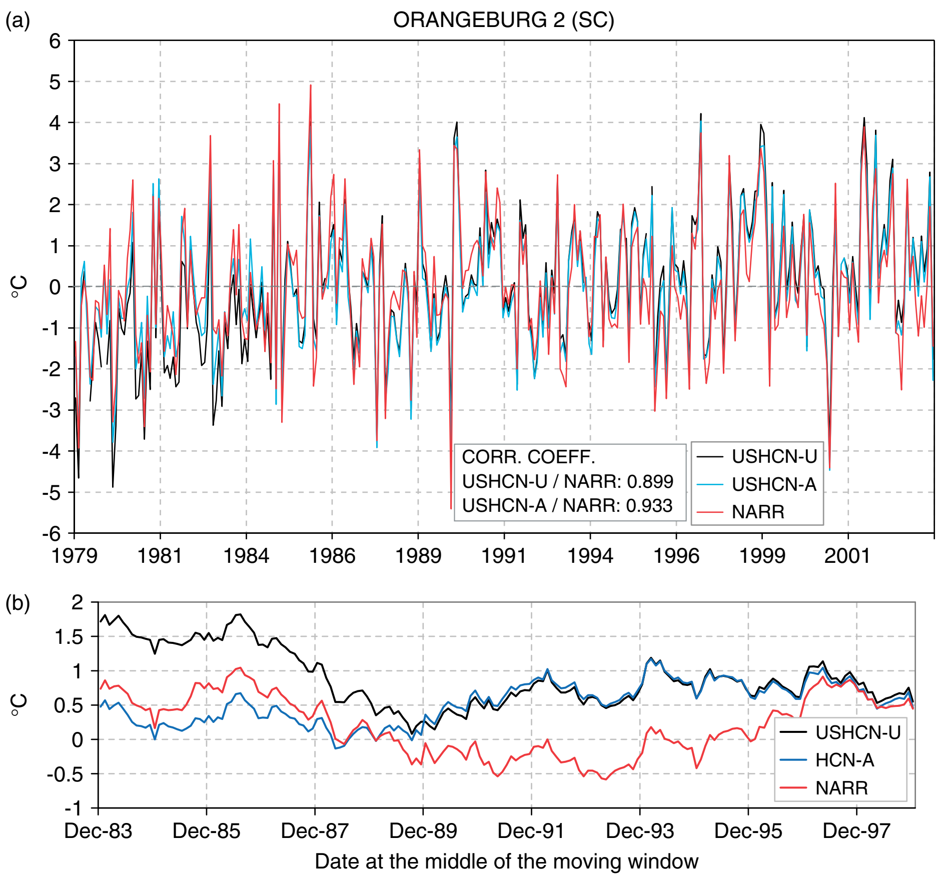

Figure 1. (a) Monthly mean temperature anomalies of observations at Orangeburg (SC). USHCN-U: unadjusted (raw) observations; USHCN-A: adjusted observations; and NARR: regional reanalysis; (b) Trends of 10-year running windows. This figure is available in colour online at www.interscience.wiley.com/ijoc

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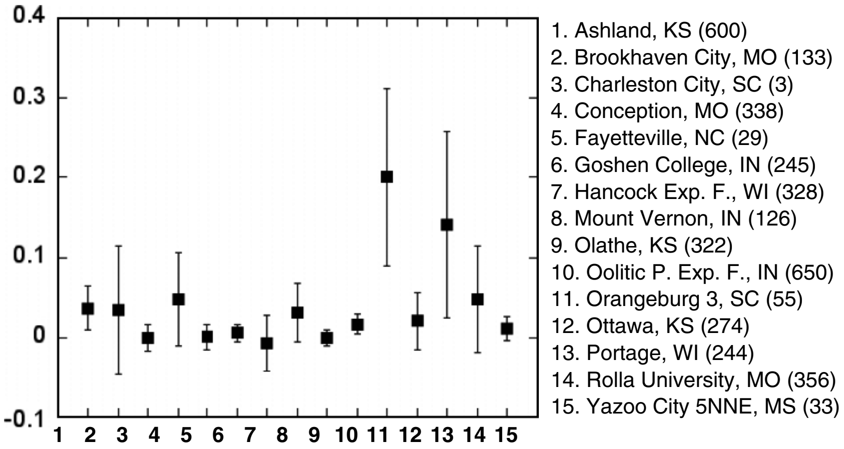

Figure 2. Difference $\hat{d}$ between MSD_1 and MSD_2 (filled squares) and their error bars (vertical lines) at 90% confidence level for selected stations (elevation in meters).

Table I. Difference $\hat{d}$ between MSD_1 and MSD_2 – mean squared differences between unadjusted station observations and NARR and adjusted station observations and NARR, respectively (units are the squares of the quantity being measured: °C/decade), and their 90% confidence intervals (CI). The land use 100-m radius around station is indicated.

Stations	Land use	$\hat{d}$	90% CI
Ashland (KS)	Cropland/grassland/urban	0.037	(0.023, 0.051)
Brookhaven City (MS)	Unknown	0.034	(0.001, 0.082)
Charleston City (SC)	Cropland/grassland	0	(−0.008, 0.009)
Conception (MO)	Urban	0.048	(0.018, 0.076)
Fayetteville (NC)	Cropland/grassland	0.001	(−0.007, 0.009)
Goshen College (IN)	Urban	0.006	(0.001, 0.012)
Hancock Exp. F (WI)	Cropland/grassland	−0.007	(−0.025, 0.010)
Mt Vernon (IN)	Urban	0.031	(0.012, 0.049)
Olathe (KS)	Cropland/grassland	0	(−0.005, 0.005)
Oolitic P. Exp. F (IN)	Cropland/grassland	0.017	(0.011, 0.023)
Orangeburg 3 (SC	Urban	0.201	(0.144, 0.255)
Ottawa (KS)	Urban	0.021	(0.004, 0.040)
Portage (WI)	Cropland/grassland	0.141	(0.083, 0.200)
Rolla University (MO)	Cropland/grassland	0.048	(0.016, 0.083)
Yazoo City 5NNE (MS)	Cropland/grassland	0.011	(0.004, 0.019)

NCEP/NCAR reanalysis (Pielke *et al*., 2007a), and show that, while station observations express local characteristics, the reanalysis effectively captures regional trends. Previous studies based on the NCEP/NCAR reanalysis have found that the reanalysis exhibits a smaller warming trend as compared to the surface observations (Kalnay and Cai, 2003; Lim *et al*., 2005; Kalnay *et al*., 2006) and as a result, the OMR trends (trend differences) are generally positive, especially for urban stations. With NARR, a station-by-station analysis reveals that this is not often the case; i.e. as seen in Table II, 9 stations out of the 15 exhibit negative OMRs when NARR is compared to unadjusted or adjusted observations, or both, regardless of the station type. For example, rural stations such as Goshen College (IN) and Hancock Experimental Farm (WI), as well as urban locations (Mount Vernon-IN and Portage-WI) show negative OMRs. This difference in the positive *versus* positive and negative trends seen in the NCEP/NCAR reanalysis and NARR-based OMR analysis could be primarily due to the finer grid spacing represented in the NARR, which may be capturing some of the local- to regional-scale changes.

Trends of 10-year running windows obtained from the gridded USHCN (adjusted) and NARR over the CONUS (Figure 3) indicate that observations and reanalysis generally not only agree in terms of variability but also show that NARR exhibits a larger trend than the adjusted USHCN over most of the study period. Consequently, the OMR time series is dominated by a negative trend, as already observed in some surface observation stations. This further confirms that, unlike other reanalysis datasets (e.g. NCEP, ERA 40), NARR has larger trends than observations.

Figure 4 shows the geographical distribution of decadal temperature anomaly trends over the CONUS. As expected, the observations (Figure 4(a)) exhibit more local scale variations and the reanalysis (Figure 4(b)) shows more uniform patterns, especially in the eastern

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Table II. Temperature anomalies and OMR decadal trends for selected stations over the eastern United States (missing data: %; trend units: °C/decade). U: unadjusted (raw) USHCN observations; A: adjusted USHCN observations; N: North American Regional Reanalysis (NARR). The asterix sign (*) denotes rural stations. Trends in bold are significant at the 5% level.

STATIONS	Missing U (%)	Trend U	Trend A	Trend N	U − N	A − N
Ashland (KS)*	3.33	**0.54**	**0.35**	0.26	0.28	0.08
Brookhaven City (MS)	7	0.25	0.18	**0.26**	−0.01	−0.08
Charleston City (SC)	5.33	**0.48**	**0.46**	0.05	0.43	0.41
Conception (MO)*	8	0.30	0.41	0.37	−0.07	0.04
Fayetteville (NC)	4	**0.41**	**0.36**	0.19	0.22	0.17
Goshen College (IN)*	2	0.32	0.34	**0.48**	−0.16	−0.14
Hancock Exp. F (WI)*	2.33	0.02	0.06	**0.49**	−0.47	−0.43
Mt Vernon (IN)	7.33	0.30	0.30	**0.53**	−0.23	−0.23
Olathe (KS)	0.66	**0.55**	**0.59**	0.40	0.16	0.19
Oolitic P. Exp. F (IN)	1.66	**0.42**	**0.43**	**0.71**	−0.29	−0.29
Orangeburg 3 (SC)	3	**0.95**	**0.58**	0.29	0.66	0.29
Ottawa (KS)*	5	**0.54**	**0.50**	0.38	0.16	0.12
Portage (WI)	1	0.35	**0.48**	**0.52**	−0.17	−0.04
Rolla University (MO)	2.66	0.26	**0.50**	0.34	−0.07	0.17
Yazoo City 5NNE (MS)	3.33	0.02	0.01	0.28	−0.25	−0.26
Average		0.38	0.37	0.37	0.01	0.00
Standard deviation		0.22	0.17	0.16		

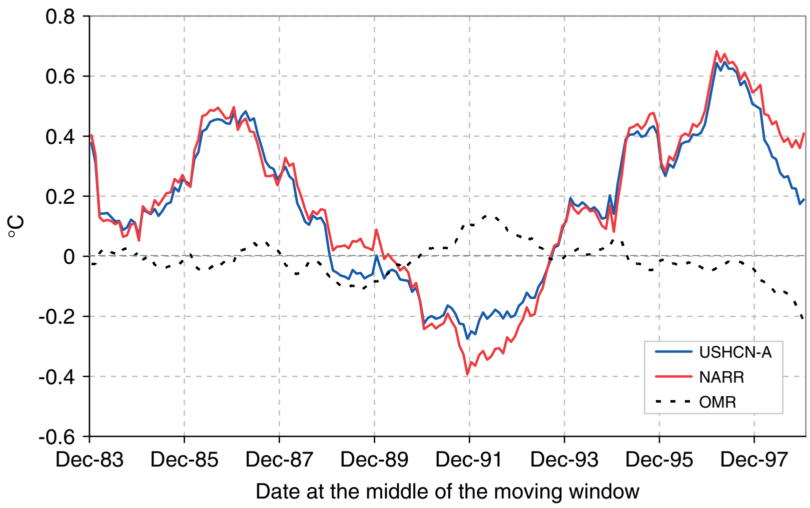

Figure 3. Trends of 10-year running windows for USHCN-A and NARR temperature anomalies averaged over the United States and the resulting OMR. This figure is available in colour online at www.interscience.wiley.com/ijoc

United States. The trends are significant at the 5% level in most of the eastern and southern United States (Figure 4(c)). Overall, USHCN and NARR agree in that they both show areas of warming trend around the Great Lakes, upper Midwest and the Northeast United States. The difference between the two samples is statistically significant (t-test, alpha = 0.05). On average, the adjusted observations and reanalysis show an increase of 0.27 °C/decade and 0.28 °C/decade respectively. As a result, the overall OMR is on average slightly negative, as confirmed by the average OMR value over the CONUS (Figure 5), but with positive and negative regions. It is mostly positive in the East Coast, and, east of the Rockies, it is negative in the northern portions of the country.

Kalnay *et al.* (2006) found qualitative agreement between the NCEP-NCAR OMR east of the Rockies, and the Hansen *et al.* (2001) 'urbanization' trend corrections, where 'rural' or 'urban' stations were defined on the basis of satellite nightlights. Figure 6 presents the NARR OMR with the Hansen *et al.* 'urban trend corrections', with the colours of the OMR reversed to facilitate the comparison. Once again, there is good qualitative agreement, even though Hansen *et al*'s urban corrections are calculated for a longer period (1950–1999). For example, over the Rockies (not included in Kalnay *et al.* (2006)), the OMR is more positive, sugesting a warming trend over mountainous regions due to surface effects, similar to the correction in Hansen *et al.* (2001). These results indicate that the differential trends based on the nightlight classification of stations, like the OMR, reflect changes in land use rather than simply urbanization, and that they can be either positive or negative.

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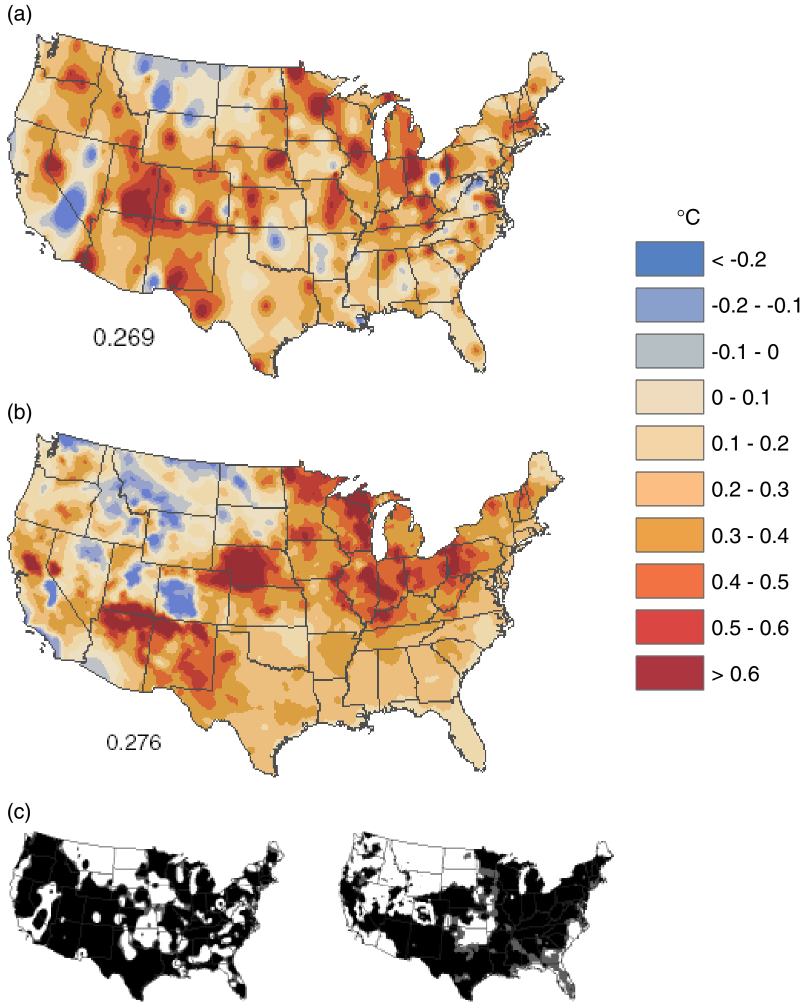

Figure 4. Mean temperature anomaly trends per decade based on monthly average data (1979–2003): (a) USHCN adjusted; (b) NARR; (c) Maps of P-values: 0.05 (black) and 0.1 (black & grey), left: USHCN adjusted and right: NARR. This figure is available in colour online at www.interscience.wiley.com/ijoc

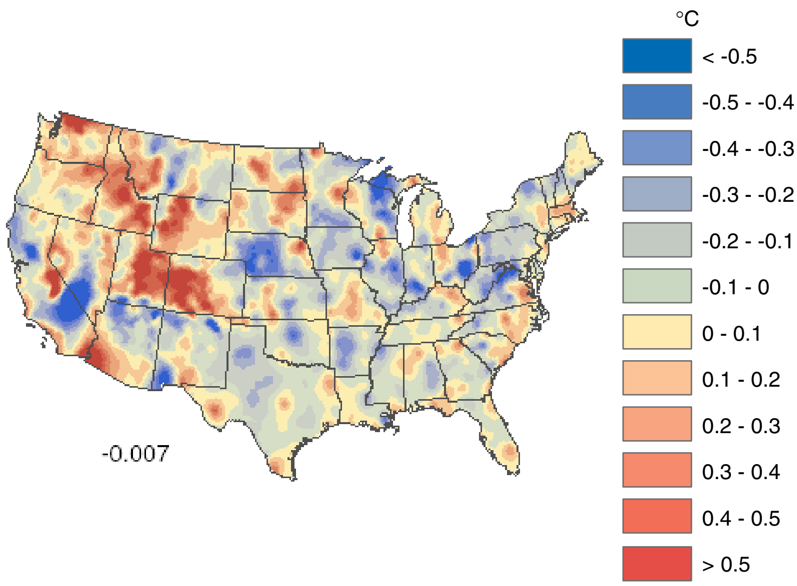

Figure 5. Adjusted observation minus reanalysis (OMR): anomaly trend differences for the 1979–2003 period. This figure is available in colour online at www.interscience.wiley.com/ijoc

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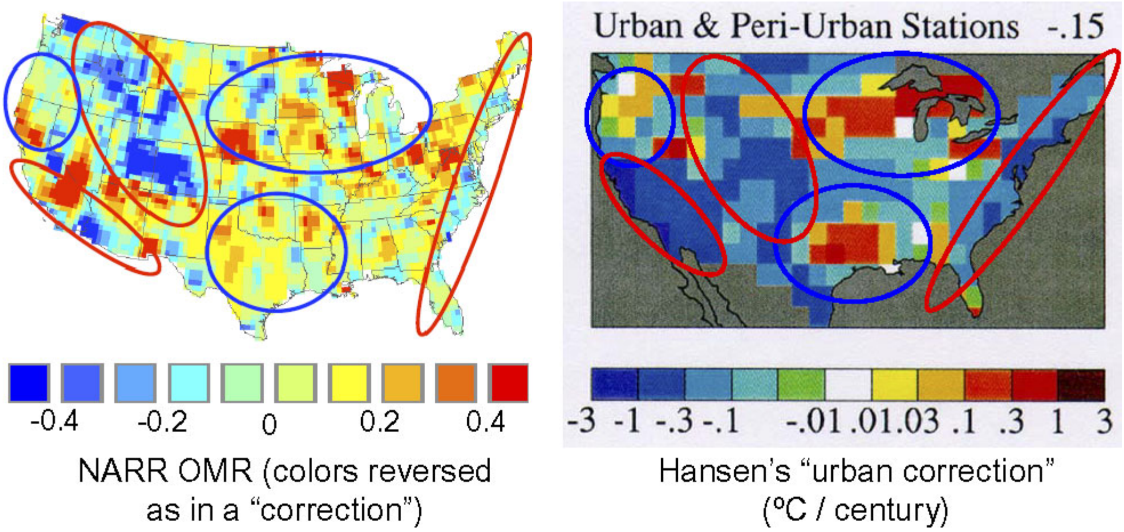

Figure 6. Comparison of the 'urbanization trends correction' derived by Hansen *et al*. (2001) using nightlights to classify stations as urban or rural, and the OMR trends with the sign changed to facilitate the comparison. This figure is available in colour online at www.interscience.wiley.com/ijoc

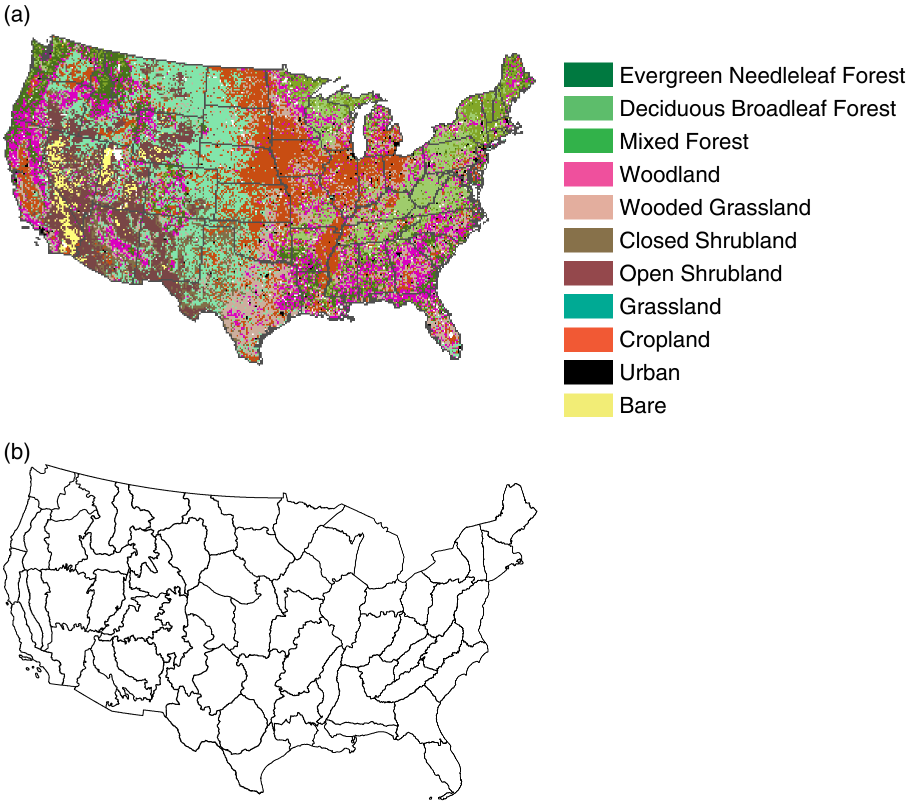

Figure 7. (a) 1-km increment land cover classification derived from AVHRR; (b) NLCD mapping zones for the CONUS. This figure is available in colour online at www.interscience.wiley.com/ijoc

3.2. Surface temperature trends with respect to LULC changes

To examine surface temperatures with respect to LULC, we associated the OMR trends with land cover types. Figure 7(a) shows the 1-km grid increment land cover classification derived from AVHRR. Only 11 land types were considered in this study. Urban areas, which represent only 0.31% of the surface, cannot be easily seen on the land cover map at this scale.

Anomaly trends per decade for the USHCN observations and reanalysis and the resulting OMRs as a function of land cover types are shown in Table III. Most land cover types show a weakly positive OMR trend per decade (0.034 °C to 0.004 °C) with the exception of wooded grassland, closed shrubland, mixed forest and deciduous broadleaf forest. Evergreen needleleaf forests, open shrublands, bare soils and urban areas exhibit the largest (positive) OMR values. These results are

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Table III. Anomaly trends per decade for observations and reanalysis and the resulting OMRs as a function of AVHRR land cover types (units: °C).

Land cover types	Area (%)	USHCN-A	NARR	OMR
Bare	11.25	0.288	0.273	0.015
Closed shrubland	8.84	0.282	0.301	−0.019
Croplands	6.97	0.274	0.271	0.003
Deciduous broadleaf forest	2.76	0.258	0.357	−0.099
Evergreen needleleaf forest	10.97	0.265	0.231	0.034
Grassland	7.96	0.244	0.238	0.006
Mixed forest	5.32	0.289	0.323	−0.034
Open shrubland	17.84	0.281	0.257	0.024
Urban	0.31	0.288	0.276	0.012
Wooded grassland	12.89	0.266	0.284	−0.018
Woodland	14.90	0.272	0.268	0.004

All trends are significant at the 5% confidence level with the exception of the NARR trends for bare and grassland types.

consistent with the findings of Lim *et al.* (2005, 2008) who point to a weak evaporation feedback over arid areas (bare soils, open shrublands) and a probable linkage to soil moisture levels. OMR trends of opposite signs for forests, also in agreement with Lim *et al.* (2005), point to a number of studies that show that needleleaf forests have low evaporative fraction as compared to deciduous broadleaf forests, which exhibit higher transpiration rates with a greater leaf area index (Baldocchi *et al.*, 2000; Baldocchi, 2005; Bonan *et al.*, 2008), thus leading to a negative temperature trend.

We analysed decadal OMR trends based on LULC changes defined by the National Land Cover Database (NLCD) 1992/2001 Retrofit Land Cover Change in 65 mapping zones over the CONUS (Figure 7(b)). Decadal OMR trends for LULC types that did not change are presented in Figure 8. Barren, urban areas and grass/shrublands show the largest warming (0.077, 0.058 and 0.054 °C respectively). Forests exhibit a less pronounced warming (0.031 °C). On the basis of the AVHRR dataset, most of the forest warming can be attributed to evergreen needleleaf forests. In contrast, there is a cooling of −0.075 °C over agricultural lands. OMR trends derived from the NLDC dataset are larger in magnitude than the AVHRR trends, and the values for each LULC type are significantly different, as attested by their error bars (95% confidence interval).

As shown in Figure 9(a), almost all areas that have experienced urbanization are associated with positive OMR trends (indicative of warming), with values ranging form 0.103 °C (conversion from agriculture to urban) to 0.066 °C (from forest to urban). The only exception is the conversion from barren areas, which shows a slight cooling (−0.014 °C), and although this trend may be questionable because of a small sample size, it agrees with the results of Lim *et al.* (2005, 2008) who observed the largest OMR trends in barren areas, followed by urban areas. These results are consistent with findings from studies such as Kukla *et al.* (1986), Arnfield (2003), Zhou *et al.* (2004) and Hale *et al.* (2006, 2008) that document the warming often associated with urbanization.

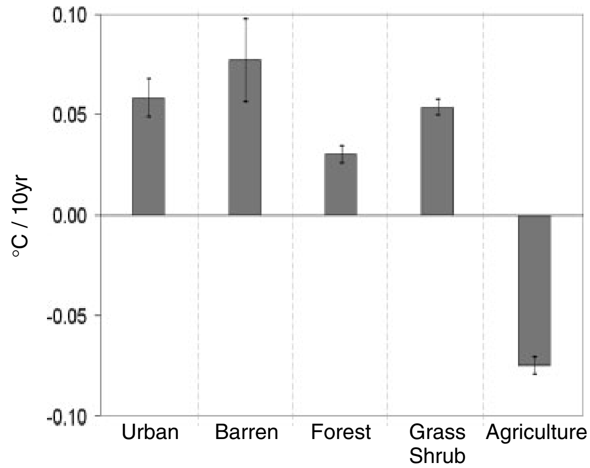

Figure 8. Decadal OMR trends of NLCD LULC types that did not change during 1992–2001. Error bars denote 95% confidence intervals.

Conversion to barren lands (Figure 9(b)) generally resulted in surface warming for all areas that were initially vegetated. The largest warming occurred in areas that changed from agriculture to barren (0.085 °C). Only moderate warming occurred in areas that shifted from forest (0.041 °C) and grass/shrub (0.039 °C). A slight cooling is recorded for locations that were initially in urban settings (−0.018 °C), but this estimate is uncertain, as attested by the large confidence intervals. Deforestation results in warming because of the shift of the surface energy partitioning into more sensible and less latent heat (Chagnon, 1992; Foley *et al.*, 2005). However, unlike studies that point to a significant increase in temperature for areas that experienced deforestation (e.g. Sud *et al.*, 1996; Lean and Rowntree, 1997; Werth and Avissar, 2004), our results suggest that only moderate warming occurred in deforested areas over the United States. Moreover, the relatively large standard deviation in this change class (0.41 °C) shows a great variability within areas that experienced deforestation.

Conversion to forest (Figure 9(c)) shows mixed results: croplands and bare soils that shifted to forests show

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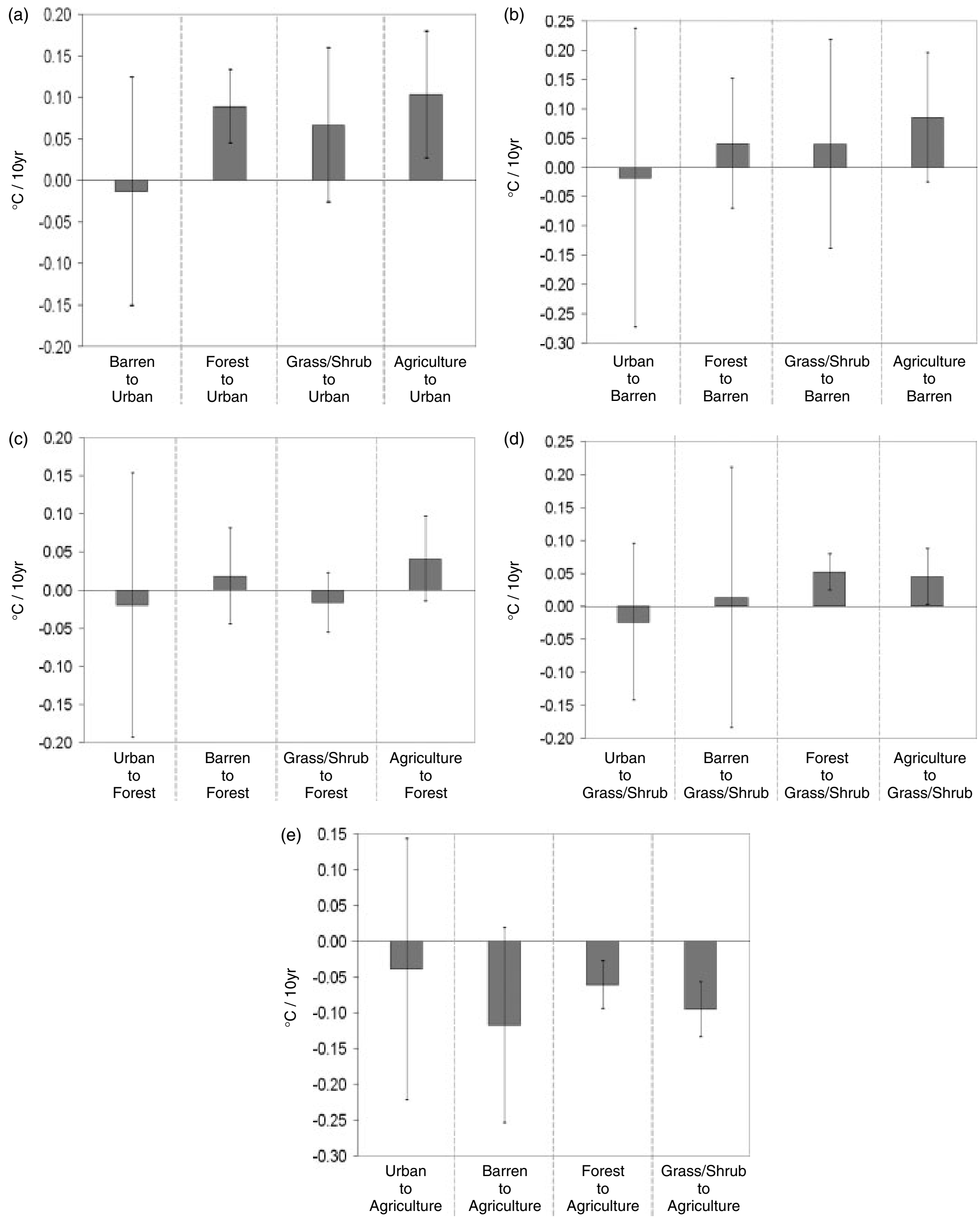

Figure 9. (a) Decadal OMR trends of NLCD LULC types that were converted to urban during 1992–2001, (b) except for barren lands, (c) except for forests,(d) except for grasslands/shrublands, (e) except for agriculture. Error bars denote 95% confidence intervals.

a moderate or small warming (0.041 and 0.018 °C respectively), while areas that were previously grassland/shrubland and urban have slightly negative OMRs (−0.016 and −0.019 °C respectively). The largest variability is found in areas that shifted from grassland/shrubland to forest (standard deviation: 0.36 °C). Results for areas that were previously urban have less reliability due to a small sample size. The warming effect of lower surface albedo that results from afforestation (Betts 2000; Feddema *et al*., 2005; Gibbard *et al*., 2005; Betts *et al*., 2007) was not seen in our results. Similarly, Hale *et al*. (2008) did not find a clear pattern in areas that experienced a clearcutting of forests.

Decadal OMR trends for areas that have been converted to grassland/shrubland are presented in Figure 9(d). With the exception of areas that were previously urban, where a slight cooling occurs (−0.023 °C), conversion to grassland/shrubland is associated with a modest warming. Trends of areas that were previously forested and agricultural (0.052 and 0.045 °C respectively) are more reliable due to a larger sample size. Areas that were previously agricultural exhibit a largest standard deviation (0.37 °C), indicating that the amount of warming/cooling varied considerably within this class.

The shift to agriculture (Figure 9(e)) results in a cooling for all conversion types and presents the largest magnitudes of cooling. The conversion of barren areas and grasslands/shrublands are associated with the largest cooling (−0.12 and −0.096 °C respectively). A moderate or relatively small cooling occurs in previously forested and barren areas (−0.061 and −0.039 °C). These results are consistent with a number of studies that show that agricultural areas are often associated with negative trends in irrigated areas (e.g. Christy *et al*., 2006; Mahmood *et al*., 2006; Roy *et al*., 2007; Lobell and Bonfils, 2008) as well as in rainfed croplands (McPherson *et al*., 2004).

4. Summary and conclusions

The OMR approach is used to investigate surface temperature trends over the CONUS. This method is made possible by the ability of reanalysis to diagnose regional-scale atmospheric conditions based on observations above the surface being assimilated into a physically consistent atmospheric model. Therefore, as the surface observations are not used in the reanalysis, the difference between the surface observation and reanalysis temperature trends represents that part of the land cover and land use change effect on temperatures which does not extend higher into the atmosphere (and thus is not seen in the reanalysis).

In this study, OMR trends derived from monthly mean temperature anomaly trends computed from USHCN observations (raw and adjusted) and the high-resolution NARR were used to (1) analyse the long term, seasonal and monthly anomaly trends over the CONUS and (2) examine the sensitivity of surface temperatures to land use land cover by using OMR trends as a function of land cover types.

As in similar previous studies (Kalnay and Cai, 2003; Zhou *et al*., 2004; Frauenfeld *et al*., 2005; Lim *et al*., 2005; Kalnay *et al*., 2006), for individual stations as well as the CONUS, the results have shown a good agreement between the observed and analysed temperature anomaly trends (high temporal correlations larger than 90%) and confirm the ability of the reanalyses to satisfactorily capture the intra-seasonal and inter-annual variability.

The analysis of anomaly and OMR trends reveals some prominent results:

1. The MSD method is efficient at assessing the performance of station temperature adjustments with respect to the reanalysis data.
2. Despite the great variability from one station to another, NARR trends exhibit much smaller spatial variations and confirm that the reanalysis effectively captures regional rather than local trends.
3. In contrast with previous studies based on global reanalysis (Kalnay and Cai, 2003; Lim *et al*., 2005), the regional reanalysis often shows a slightly larger trend than the observations and, as a result, the OMR trend is on the average negative. However, the adjusted observations, which are mostly used in this study, are known for reducing the differences with the reanalysis. NCEP/NCAR global reanalysis and the newer NARR are two key datasets in climate studies and there is a large body of literature based on global reanalysis. The differences between results obtained from both datasets suggest the need of conducting comparative studies that may provide further understanding of processes relevant to climate studies.
4. Our results on a station-by-station basis did not suggest significant differences between rural and urban trends, rather they were dependent on regional land use, and agreed better with the classification based on nightlights used by Hansen *et al*. (2001). Kalnay and Cai (2003) found a strong urban–rural signal, but they used different datasets, a different study area (eastern United States) and different period (they also included the 1960–1990's trends). Future analysis with more stations would be therefore useful in understanding the urban–rural temperature differences.

Our analysis of OMR trends with respect to land types using the AVHRR dataset indicate that evergreen needleleaf forests, open shrublands, bare soils and urban areas exhibit the largest increasing trends. Grasslands, woodlands and crops are also modestly positive while wooded grassland, closed shrubland, mixed forest and deciduous broadleaf forest show cooling trends. Our results vary from Lim *et al*. (2005) in that we found much weaker positive OMR trends, e.g. 0.034 *versus* 0.3 °C for bare soils when using regional instead of global reanalysis.

The NLCD 1992/2001 Retrofit Land Cover Change offers a unique opportunity of examining the relationships between OMR trends and the type of land surface by taking into account the dynamic nature of LULC. We found that OMR trends derived from the NLCD dataset display approximately the same patterns as the ones obtained from the 'static' AVHRR dataset, but with a larger magnitude. For example, decadal OMR trends of bare and urban areas for AVHRR are 0.015 and 0.012 °C, whereas for non-changed NLCD they are 0.113 and 0.072 °C respectively. This discrepancy is probably explained by the fact that the AVHRR dataset reflects both non-changed and changed signals.

Moreover, the breakdown of the NLCD dataset into areas that did not change *versus* areas that were converted shows that land use conversion often resulted in more warming than cooling. With the notable exception of agricultural lands, most of the negative trends were derived from conversion types with a small sample size (e.g. the conversion of urban areas). The warming effect generally associated with LULC changes is confirmed in

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a number of recent studies (e.g. Hale *et al*., 2006, 2008; Kalnay *et al*., 2006; Pielke *et al*., 2007b).

Our results suggest that for both non-changed and converted land types, agriculture, urbanization and barren soils offered the clearest patterns in terms of sign and magnitude of the OMR trends. Conversion to agriculture resulted in a strong cooling. Conversely, all conversions of agricultural lands resulted in warming. Urbanization and conversion to bare soils were also mostly associated with warming. We conclude that these LULC types constitute strong drivers of temperature change.

Deforestation generally resulted in warming (with the exception of a shift from forest to agriculture) but no clear picture emerged for afforestation. Within each land use conversion type, a great variation of warming/cooling was observed, as attested by relatively large standard deviations. In addition, our analysis shows that there is not always a straightforward relationship between the different types of conversions: for example, (1) both conversion of urban to barren and the opposite resulted in slightly negative OMRs; (2) there was a weak warming of areas that shifted from bare soils to grassland/shrubland and for the opposite as well and (3) both conversion from forest to grassland/shrubland and the opposite were associated with a weak warming. In a number of cases, our estimates were hampered by the lack of significance due to a small number of samples. All these considerations lead us to conclude that the effects of LULC changes on temperatures trends are significant but more localized studies need to be conducted using high-resolution datasets.

Our results were limited due to the missing data often typical of the USHCN raw (unadjusted) observations over the study period. As a result, the trends obtained from this dataset cannot be as accurate as the ones derived from the adjusted observations and reanalysis, even though the anomaly trends at station level showed a good agreement between observed and analysed temperature anomalies. Such a constraint has resulted in spurious trends when we tried to convert the raw observations into gridded data.

However, our results further confirm the robustness of the OMR method for (1) capturing the climate variability at various time scales; (2) detecting non-climatic changes at the station level, including observation practices and land use changes, (3) evaluating the impacts of adjustments performed on raw observations and, most importantly, (4) providing a quantitative estimate of additional warming trends associated with LULC changes at local and regional scales. Despite some uncertainties, the effects of LULC dynamics on temperature trends are well captured by the OMR method, which shows a strong relationship with LULC changes. Furthermore, this study demonstrates that using datasets that reflect the dynamical nature of LULC (such as the new NLCD 1992–2001 Retrofit Land Cover Change) offers unique opportunities for assessing the impacts of LULC change on temperature trends at local and regional scales.

In conclusion, *in situ* observed surface temperatures are affected by local microclimate and non-climatic station changes, and also by the larger scale landscape within the region. By using multiple station observations, one can evaluate the part of the signal in the surface temperature data that is spatially correlated with the regional land cover/land cover characteristics. By comparing the surface temperature data with the reanalysis temperature data diagnosed at the same height, the degree to which the land use/land cover change effect on temperatures does not extend higher into the atmosphere can be assessed. The degree to which this effect occurs depends on landscape type (due to different boundary layer interactions with the free atmosphere above).

The need to separate the local from the regional land use change effect on the temperature record does merit further study, as the latter is a regional climate forcing effect, while the local microclimate and non-climatic station effects are a contamination of the temperature data in terms of constructing regional scale temperature trends.

Because most of the warming trends that we identify can be explained on the basis of LULC changes, we suggest that in addition to considering the well-mixed greenhouse gases and aerosol-driven radiative forcings, multi-decadal and longer climate models simulations must further include LULC changes. In terms of using long-term surface temperature records as a metric to monitor climate change, there also needs to be further work to separate the local microclimate and non-climate station effects from the regional LULC change effects on surface temperatures.

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Appendix: Confidence Intervals for Parameters Computed from Observed Data

The value of $\hat{d}$ is a point estimate of the true value of the parameter of interest d. To learn how much importance

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is reasonable to attach to $\hat{d}$, it is common to provide a confidence interval (CI) that contains d with a certain coverage probability (0.90 in our study). The unknown value of d may be considered positive if its CI contains only positive numbers, as is the case for 11 out of the 14 stations in our analysis. Note also that it is incorrect to compare MSD_1 and MSD_2 by computing CIs for each and then considering MSD_1 and MSD_2 different if their CIs do not overlap (see, e.g. Schenker and Gentleman, 2001).

Classical statistical methods for computing CIs are based on assumptions about the data-generating mechanisms that are rarely met in climatology. One such assumption is that observations follow a Gaussian distribution. It has been realized, however, that even small deviations from the assumptions may result in misleading inference (e.g. Wilcox, 2003). Fortunately, modern computer-intensive resampling (bootstrap) techniques (e.g. Efron and Tibshirani, 1993; Davison and Hinkley, 1997; Lahiri, 2003) permit obtaining reliable inference without making questionable assumptions about the data. The CIs in Table I were computed using the basic bootstrap. This implies, however, that the observations are independent and identically distributed, while climatological variables are typically serially correlated. It is known that bootstrap may underestimate the width of CIs in this case (e.g. Zwiers, 1990). Thus, our results regarding statistical significance may need refinement, which could be accomplished by employing another bootstrap technique, subsampling (Politis *et al*., 1999), whose practical implementation is now under active development (e.g. Gluhovsky *et al*., 2005; Gluhovsky and Agee, 2007).

The same applies to our results on uncertainties in trends that may, in this respect, be considered as incremental. In time series analysis, the assumption is often made that the trend is linear, while the residuals from the trend follow a linear autoregressive model. Bloomfield (1992) fitted such a model and a linear trend to an 1861–1989 temperature time series and found a linear trend of 0.58 with 95% (classical) CI, (0.37, 0.76). More recently, Craigmile *et al*. (2004) and Kallache *et al*. (2005) employed wavelets to assess trends while modeling fluctuations with fractional ARIMA models that incorporate long-range dependence.

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