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Impacts of land cover transitions on surface temperature in China based on satellite observations

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Abstract

China has experienced intense land use and land cover changes during the past several decades, which have exerted significant influences on climate change. Previous studies exploring related climatic effects have focused mainly on one or two specific land use changes, or have considered all land use and land cover change types together without distinguishing their individual impacts, and few have examined the physical processes of the mechanism through which land use changes affect surface temperature. However, in this study, we considered satellite-derived data of multiple land cover changes and transitions in China. The objective was to obtain observational evidence of the climatic effects of land cover transitions in China by exploring how they affect surface temperature and to what degree they influence it through the modification of biophysical processes, with an emphasis on changes in surface albedo and evapotranspiration (ET). To achieve this goal, we quantified the changes in albedo, ET, and surface temperature in the transition areas, examined their correlations with temperature change, and calculated the contributions of different land use transitions to surface temperature change via changes in albedo and ET. Results suggested that land cover transitions from cropland to urban land increased land surface temperature (LST) during both daytime and nighttime by 0.18 and 0.01 K, respectively. Conversely, the transition of forest to cropland tended to decrease surface temperature by 0.53 K during the day and by 0.07 K at night, mainly through changes in surface albedo. Decreases in both daytime and nighttime LST were observed over regions of grassland to forest transition, corresponding to average values of 0.44 and 0.20 K, respectively, predominantly controlled by changes in ET. These results highlight the necessity to consider the individual climatic effects of different land cover transitions or conversions in climate research studies. This short-term analysis of land cover transitions in China means our estimates should represent local temperature effects. Changes in ET and albedo explained <60% of the variation in LST change caused by land cover transitions; thus, additional factors that affect surface climate need consideration in future studies.

1. Introduction

Climate change is one of the greatest challenges facing our planet. The impacts of climate change affect every aspect of our lives, including human health, agriculture, coasts, and forest and water resources. Human activities have been found to be the dominant mechanisms responsible for recent climate change, particularly through the combustion of fossil fuels and changes in land use (Hegerl *et al* 2007).

As one of the major but poorly understood drivers of climate change, land use/land cover change (LULCC) affects the climate system through both biogeochemical effects (mainly the carbon cycle and associated changes in atmospheric carbon dioxide concentration) and biophysical effects due to the modification of land surface albedo, evapotranspiration, and surface roughness (Brovkin *et al* 2006, Pielke *et al* 2011, Boisier *et al* 2012, Sitch *et al* 2005, Pongratz *et al* 2010, Brovkin *et al* 2013, Mahmood *et al* 2014). Biogeochemical effects are reasonably well established, although their magnitudes still require accurate quantification. In contrast, biophysical effects are more uncertain and spatially dependent on location; thus, they require further attention (de Noblet-Ducoudré *et al* 2012). The main biophysical effects might be manifest via evapotranspiration (ET) and surface roughness in the moist tropics, and via surface albedo in mid- and high-latitude regions (Betts *et al* 2007). Globally, the albedo effect is dominant (Davin and de Noblet-Ducoudré 2010), with an estimated radiative forcing of -0.15 ± 0.10 W m^{-2} during 1750–2011 (Myhre *et al* 2013). This estimated impact is relatively small because LULCC is a highly regionalized phenomenon; however, local effects of LULCC due to changes in albedo can be significant (Pielke *et al* 2002, Rosenzweig *et al* 2008).

Methods used to explore the biophysical climate effects of LULCC can be categorized into model experiments and observation-driven assessments (Perugini *et al* 2017). The climate model can effectively simulate the interaction between the land surface and the atmosphere, and thus provide detailed physical explanations of the climatic impacts of LULCC. However, due to the uncertainties in underlying physical processes, parameterizations, and input data, large discrepancies or even conflicting results were found in simulated climate effects (Pitman *et al* 2009), which has driven the development of observation-based benchmarking methods (Boisier *et al* 2013, Boisier *et al* 2012). Compared with model simulations, observational-based methods can provide observational evidence of climate change and the changes in biophysical parameters (e.g. albedo and evapotranspiration) associated with land cover changes, but have difficulties of inferring causality existed in the land surface and atmosphere interaction.

Using the observation minus reanalysis method, Kalnay and Cai (2003) analyzed the sensitivity of the surface climate effects of LULCC. They reported that little surface information was assimilated into the reanalysis data, and that regional surface processes associated with LULCC, which were not included in the reanalysis, affected the *in situ* observations (Wang *et al* 2013). Using the same method, Zhou *et al* (2004) and Zhang *et al* (2005) found observational evidence for a significant urbanization effect on surface temperature in China. It should be noted that these studies did not separate the individual effects of land use change types (e.g. urbanization, deforestation, and reforestation), nor could they explore the physical processes involved in how land use changes affect surface temperature (Hale *et al* 2008).

Similar to the observation minus reanalysis method, some studies have quantified the relationship between LULCC and various climatic factors by calculating the differences in surface temperature between areas with contrasting land cover types, either from *in situ* measurements or satellite-derived observations (Li *et al* 2015, Zhao and Jackson 2014, Peng *et al* 2014). However, the substitution of space for time in surface temperature variations might produce biased results, since spatial gradients in surface climate cannot be attributed to changes in land cover alone (Alkama and Cescatti 2016, Lee *et al* 2011). Instead of using the space-for-time analogy, Alkama and Cescatti (2016) undertook a time series analysis using satellite observations that disentangled the effects of forest cover changes from the global climate signal. They found a biophysical mean warming due to variations in forest cover during 2003–2012. Following this study, we performed a time series analysis that separated the effects of land cover transitions from regional or large-scale weather and climate signals, with the aim of providing observational evidence of the climatic effects of land cover transitions over China based on satellite observations, and furthermore, quantifying the degree to which major land cover transitions could influence surface temperature with satellite observations, in particular through modifications of the surface albedo and ET.

In terms of LULCC, previous studies exploring the associated climatic effects have focused mainly on urbanization and forest cover change, while other types of LULCC have received comparatively little attention, even though they comprise the majority of land cover change and transition types. Here we considered multiple types of land cover transition, including but not limited to urbanization and forest cover change. Therefore, another objective of this study was to explore the impacts of different land cover transition types on surface temperature, and examine whether different land cover transitions in China would result in different surface temperature changes.

2. Data and methods

2.1. Land use and land cover change in China

Several datasets have been used to describe land use and land cover in China, including the national land resources inventory data sponsored by the Ministry of Land and Resources, statistical data from the State Statistical Bureau, the International Geosphere-Biosphere Programme DIScover dataset produced from 1 km resolution Advanced Very High Resolution Radiometer data, and China's land use/cover datasets (CLUDs) (Liu *et al* 2005). We selected CLUDs to quantify land use and land cover changes and the associated transitions in China, because of their higher accuracy and detailed spatial characterization of land use status (Liu *et al* 2014). The CLUDs are made available for every five years from the late 1980s. To build each dataset, over 500 Landsat TM images were interpreted into 25 land use/land cover categories at the scale of 1:100 000, after first being georeferenced and orthorectified, and then they were converted into a 1 km raster database by calculating area percentages for each land use category within every cell (Liu and Buhe 2000, Liu *et al* 2002). The 25 land cover classes were grouped into six aggregated classes: cropland, woodland, grassland, water bodies, unused land, and built-up areas including urban areas. The definition of each land cover class was given in Liu *et al* (2005). In this study, water bodies and unused land were assimilated into one type named others, since we are interested in land use changes and transitions related to cropland, woodlands, grassland, and built-up areas.

Based on the CLUDs, the land use change measurements of a single type (e.g. cropland, grassland, forest, or urban), as well as the transitions between these land use types from the late 1980s (about 1990) to 2005 were calculated (supplementary data available at stacks.iop.org/ERL/13/024010/mmedia). Since the CLUDs only report the percentage of each grid cell that was cropland (or grassland, forest, urban) without specifying where the corresponding land use type was located within the grid cell, the transitions between land use types could not be determined uniquely (Hurtt *et al* 2006). Here, we assumed the land use/cover type with the maximal negative change proportion transitioned to the type with the maximal positive change proportion, but ignored transitions with maximal change areas of <0.05%. To examine whether the observed transitions were driven by statistical systematic processes or random processes, we detected the signals of land cover change or transition using the same method as in previous studies, which adopted the Chi-square approach to compare the observed transition matrix with an expected matrix generated under random processes (Ouedraogo *et al* 2016, Braimoh 2006, Pontius *et al* 2004). Unlike previous studies that have detected systematic and random land cover transitions in a landscape, we performed a pixel-wise detection at the 0.05° scale. Using this method, we separated spurious land cover transitions from the experienced systematic transitions on a pixel level. Thus, we focused on the most dominant signals of LULCC and the associated transitions between land use and land cover types in China. Details on the detection of systematic and random land cover transitions were provided in the supplementary information.

2.2. Satellite data products

The Global Land Surface Satellite (GLASS) albedo products were used to describe changes in surface albedo due to LULCC or land cover transitions. The GLASS albedo is a gapless, long-term continuous, and self-consistent dataset with an accuracy similar to that of the Moderate Resolution Imaging Spectroradiometer (MODIS) product (Liu *et al* 2013, Liang *et al* 2014, Liang *et al* 2013). The GLASS albedo from 2000–2012 is derived from MODIS data, and it has 1 km spatial resolution and 8 d temporal resolution. It provides both white-sky albedo and black-sky albedo. Here, we used the white-sky albedo because it is independent of solar and view angles; thus, it could be compared spatially and temporally (Gao *et al* 2005). The 8 d albedo data at 1 km resolution with sinusoidal projection were first converted to WGS84 geographical coordinates and then aggregated into monthly albedo data with spatial resolution of 0.05°.

The monthly MOD16 ET product with 0.05° resolution, which was acquired from the University of Montana's Numerical Terra Dynamic Simulation Group (www.ntsg.umt.edu), was used to represent changes in ET due to land cover changes and transitions. It was derived from MODIS land cover, albedo, FPAR/LAI data, and global surface meteorology from the GMAO using Mu *et al*'s improved ET algorithm (Mu *et al* 2011). Similar to the albedo data, MODIS ET data from 2001–2012 were used.

Two monthly climate modelling grid LST products of MODIS (i.e. MOD11C3 and MYD11C3) with 0.05° spatial resolution provided the daytime and nighttime monthly averages of LST in this analysis. MOD11C3 products are retrieved from MODIS on the Terra (morning) platform, which has overpass times at 10:30 and 22:30 local time, while MYD11C3 products are retrieved from MODIS on the Aqua (afternoon) platform with overpass times at 01:30 and 13:30 local time, i.e. close to the times of daily minimum and maximum temperature (Wan 2014). However, some studies have suggested that the time difference between the moment of satellite overpass and the time of observed maximum or minimum air temperature was not critical in correlations between air temperature and LST (Mostovoy *et al* 2006, Zhang *et al* 2011). In this study, we tested the performance of MODIS Terra and MODIS Aqua in quantifying LST for all land cover transition types and found no substantial differences in using the MOD11C3 and MYD11C3 products. Considering that Aqua and Terra LST data are available from July 2002 and early 2000, respectively, we selected the MOD11C3 product for this analysis.

All these monthly variables were aggregated to seasonal and annual means. Furthermore, to minimize the influence of topography and land surface properties on the spatial variation of these variables, we used albedo, ET, and LST anomaly relative to 2001–2012 in the analysis, rather than the original time series at monthly, seasonal, and annual scales.

2.3. Background climate

Some studies have suggested that the climatic impacts of LULCC are largely affected by background climate or weather (Pitman *et al* 2011, Li *et al* 2016). To estimate the impacts of land cover change on surface climate, the natural climate variability in the background climate signal must be screened out. In this study, the Köppen–Geiger climate classification, one of the most widely used climate classification systems, was adopted to characterize the regional climate in China

(Peel *et al* 2007). More details were given in the following section (section 2.4).

2.4. Analysis

To evaluate the impacts of observed land cover transitions on surface temperature in China, we first explored the spatial patterns of LST change and their spatial coupling with land cover transitions by examining the LST differences between the periods before and after the transition. We applied three consecutive years of surface temperature at an annual timescale to quantify the LST changes over land cover transition areas. The LSTs of 2001, 2002, and 2003 were averaged to represent the LST around 2001, and the average of the LSTs of 2005, 2006, and 2007, and that of 2010, 2011, and 2012 represented the LST around 2006 and 2011, respectively. Since the observed LST changes contained background regional interannual variations unrelated to land cover transitions, we created a regional mean annual LST anomaly averaged over all the pixels in the same Köppen–Geiger climate zone (i.e. one value for each climate zone in each year). We then subtracted this mean from the original anomalies to factor out the influence of background climate. After removing the natural LST variability, the spatial variability of pixel-wise LST changes (ΔLST) relative to the regional mean change could be identified. Changes in albedo (ΔAlbedo) and ET (ΔET) due to land cover transitions were reprocessed using the same method as used for LST (Method I). We measured the influence of the chosen methodology in calculating the natural variabilities of LST, ET, and albedo in each climate zone based on the quantification of ΔLST, ΔET, and ΔAlbedo. This was achieved by employing alternative methods to extract the natural variabilities of LST, ET, and albedo in each climate zone. The pixels within each climate zone that did not experience land cover transitions during 1990–2000 and during 2000–2005 were averaged and these averages were subtracted from the original anomalies (Method II and Method III) as a comparison.

We then conducted partial correlation analysis to measure the association or correlation of ΔET and ΔAlbedo with ΔLST while controlling the other factor (Schielzeth 2010). Following this, we regressed ΔLST with ΔET and ΔAlbedo with multiple linear regression models. We undertook dominance analyses of the multiple linear regression models to evaluate the individual contributions of ΔET and ΔAlbedo to ΔLST, and quantify the degree to which each land cover transition could modify the surface temperature through changes in surface albedo and ET (Azen and Budescu 2003, Budescu 1993). General dominance weights were summed to the total model R-square and thus, they could provide the decomposition of the total predicted variance.

We performed quantile regressions to explore how the two dominant biophysical effects (via ΔET and ΔAlbedo) exerted on ΔLST extremes, and investigated whether ΔET and ΔAlbedo influence ΔLST differently for ΔLST with higher rates and for ΔLST with lower rates (Cade and Noon 2003). As an extension to the ordinary least squares regression, quantile regression does not require any assumptions regarding the distribution of the regression residuals, and it is not affected by outliers or skewness in the distribution of ΔLST. For this reason, quantile regression can provide robust interpretation and sufficient information regarding the relationships between the predicted variables (i.e. ΔET and ΔAlbedo) and ΔLST. In this study, quantile regression was employed to assess the associations of the variables at the 10th, 25th, 50th, 75th, and 90th percentiles of ΔLST in each area of land cover transition.

Table 1. Percentage of pixels that experienced land use change during 1990–2005.

Land use types	Decrease (%)	Increase (%)
cropland	20	23
woodland	14	19
grassland	50	19
built-up	2	9
others	14	30

3. Results and discussion

3.1. LULCC and land cover transitions in China

We found 14% of pixels underwent systematic land use transitions from around 1990–2005, and grassland degradation accounted for the greatest proportion of transitions during this period (table 1). Among the land use types considered in this study, the transition of grassland to other types (or unused land) accounted for 21% of all transitions, followed by the transition to cropland (15%) and to forest (14%). Figure 1 shows the spatial distribution of major land cover transitions and the corresponding transition amounts in China during 1990–2005, where FC, GC, GF, CG, OG, CU, and GO represent the transition from forest to cropland, from grassland to cropland, from grassland to forest, from cropland to grassland, from other types to grassland, from cropland to urban, and from grassland to other types, respectively. Of these transition types, large gains in cropland occurred in Northeast China at the expense of forest and grassland (FC and GC), particularly in Heilongjiang Province. The Beijing–Tianjin Metropolitan Area, Yangtze River Delta, and Pearl River Delta regions all experienced rapid urban expansions, which were mainly converted from original cropland.

3.2. Impacts of land cover transitions on surface temperature

Figure 2 shows the changes in LST, albedo, and ET during 2001–2012 derived from the annual averages of 2010–2012 minus those of 2001–2003. Significant changes in annual mean daytime LST, nighttime LST, albedo, and ET were detected. They were spatially

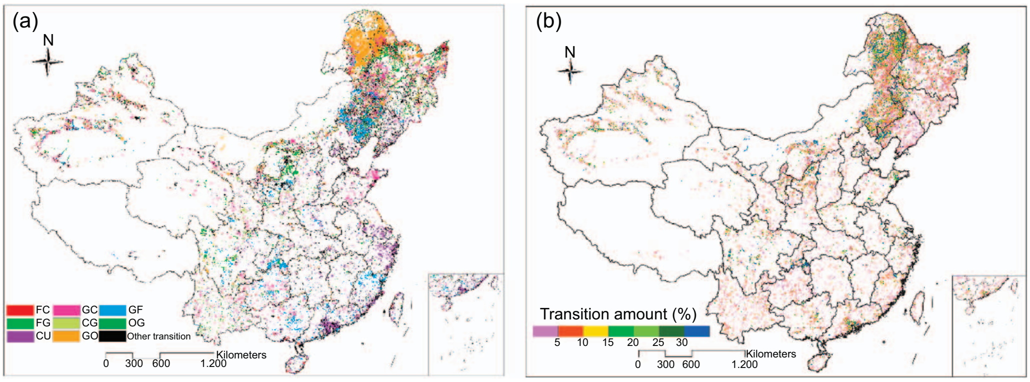

Figure 1. Land use transitions (*a*) and transition amounts (*b*) in China during 1990–2005.

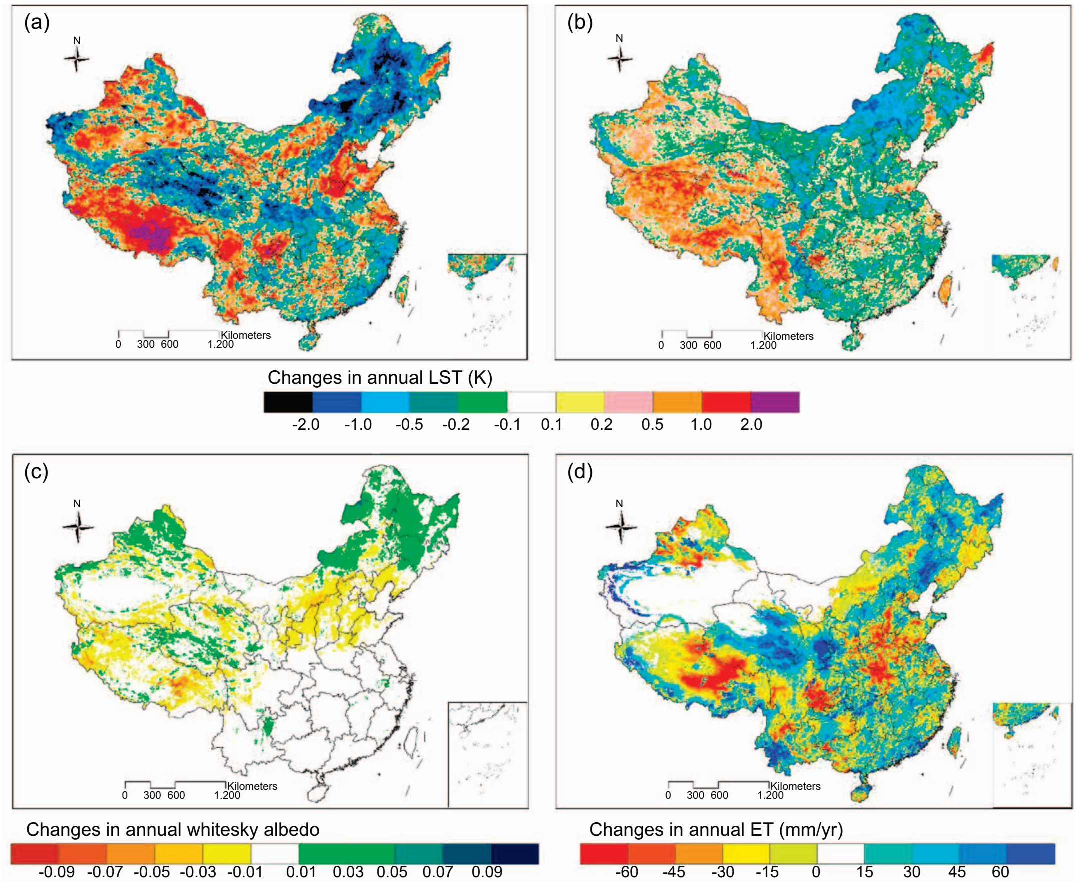

Figure 2. Changes in annual daytime LST (K) (*a*), nighttime LST (K) (*b*), albedo (*c*), and ET (mm yr^{-1}) (*d*) during 2001–2012, as derived from the comparison of 2001–2003 with 2010–2012 for different climate zones. Regional inter-annual variability for each climate zone was removed to emphasize the relative LST, albedo, and ET changes at the pixel level.

clustered and not coupled well with the spatial distribution of land cover transitions (figure 1 and figure 2). As can be seen, LST increased or decreased not only in areas where transitions occurred but also in areas without transition; similar findings were derived for the changes in albedo and ET as well. This indicates that the impacts of LULCC or land cover transitions on LST were, on the whole, relatively limited, and that other factors might predominantly affect LST dynamics (Zhou *et al* 2012). Moreover, in the areas where experienced the same land cover transitions (e.g. urbanization in Shanghai), changes in annual daytime and nighttime LST were not always consistent in spatial distribution, and the corresponding reasons were complex (Weng 2009).

The three methods described in section 2.4 produced similar results of ΔLST in land cover transition regions, which indicate the insensitive of the reference LST anomaly to land cover transitions (figure S1). One possible reason for this phenomenon is that the

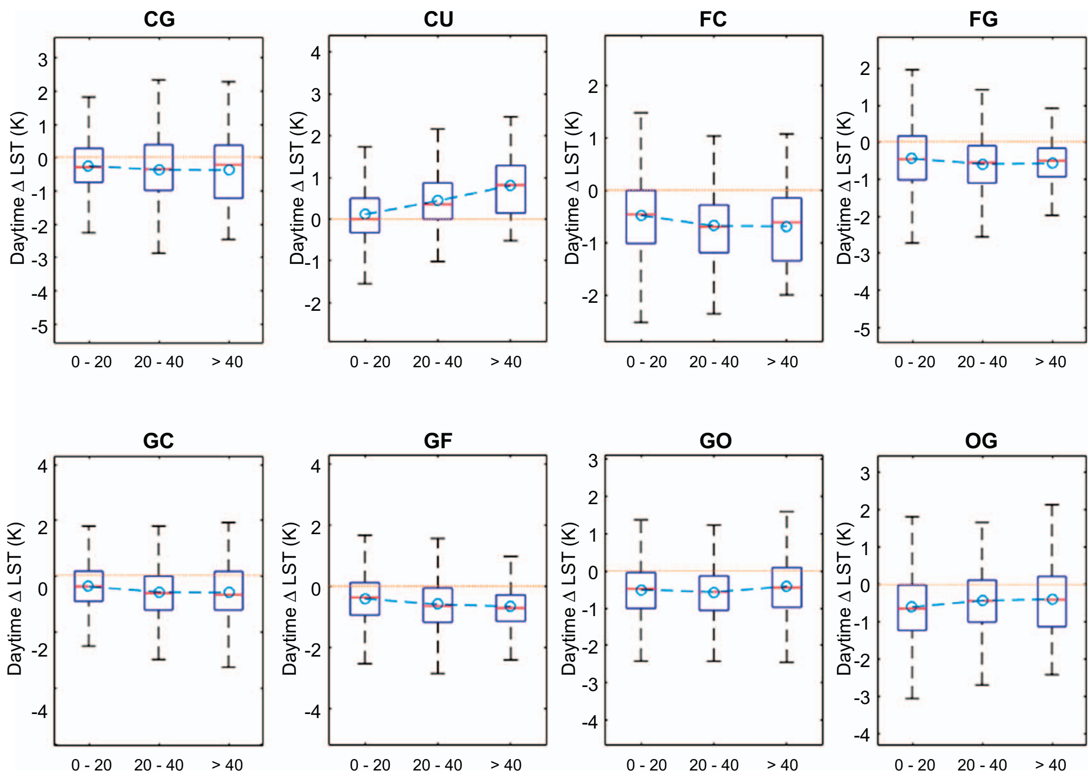

Figure 3. Boxplots of annual mean changes in daytime LST (K) during 2001–2012 for different land cover transition (%) bins due to each type of land cover transitions in China. For each box, the central red mark is the median, the edges of the box are the 25th (Q1) and 75th (Q3) percentiles, and the whiskers extend from the lowest value within the lower limit (Q1−1.5 (Q3–Q1)), to the highest value within the upper limit (Q3+1.5 (Q3–Q1)). The blue circle represents the average values of daytime LST change for different land cover transition bins.

pixels that experienced systematic land cover transitions accounted for only a small proportion of the areas in China. Therefore, the following results were based on ΔLST estimated using Method I. Linking the annual mean ΔLST with land cover transitions, we found that CU increased the daytime LST by 0.18 K on average, and nighttime LST by 0.01 K, which was in accordance with previous studies that identified similar warming effects associated with local urbanization in China, although the warming magnitudes were different (Zhao *et al* 2014, Li *et al* 2010, Hu *et al* 2015, Sun *et al* 2016, Wang *et al* 2015). In contrast to CU, FC tended to cool the surface temperature by 0.53 K during daytime and by 0.07 K during nighttime. Previous studies also observed the cooling effects of agricultural development (Zhao *et al* 2016, Zhu *et al* 2012). A global modeling study related such cooling effects to irrigation in agricultural regions, regardless of their climate regimes (Lobell *et al* 2006). GF also caused decreases in daytime and nighttime LST with average values of 0.44 and 0.20 K, respectively. If we consider only transitions with amounts >40% within a pixel, the average increases in LST due to CU reached 0.81 K during the daytime and 0.19 K at night. Similarly, the mean daytime ΔLST caused by FC was −0.69 K, and the corresponding nighttime ΔLST was 0.02 K, i.e. a signal of opposite sign but with smaller magnitude than the daytime cooling. For GF, the consequent ΔLST was −0.65 K during the daytime and −0.31 K at night (figure 3 and figure 4).

Figure 3 and figure 4 show the distributions of annual daytime ΔLST and nighttime ΔLST during 2001–2012, including the medians and their confidence intervals, due to land cover transitions in China. In general, daytime warming (or cooling) was stronger than nighttime warming (or cooling), which is consistent with the findings of some previous studies (Hu *et al* 2015, Sun and Kafatos 2007). Boxplots of annual mean changes in LST revealed that the median value for daytime ΔLST caused by CU transition was 0.04 K. However, for FC, the corresponding median value of daytime ΔLST was −0.52 K, while for GF, it was −0.45 K, i.e. close to the mean average value of daytime ΔLST. Meanwhile, the values of ΔLST during both daytime and nighttime caused by CU, FC, and GF transitions varied depending on transition amounts. The values of ΔLST in areas with transition amounts >40% as a consequence of CU, FC, and GF transitions reached 0.82, −0.61, and −0.70 K, respectively, and the analogous changes in nighttime LST were 0.17, −0.15, and −0.41 K, respectively. However, the phenomena that daytime and nighttime values of ΔLST were more significant for transition bins with larger transition amounts were not observed in regions with CG, FG, GC, GO, and OG transitions (figure 3 and figure 4).

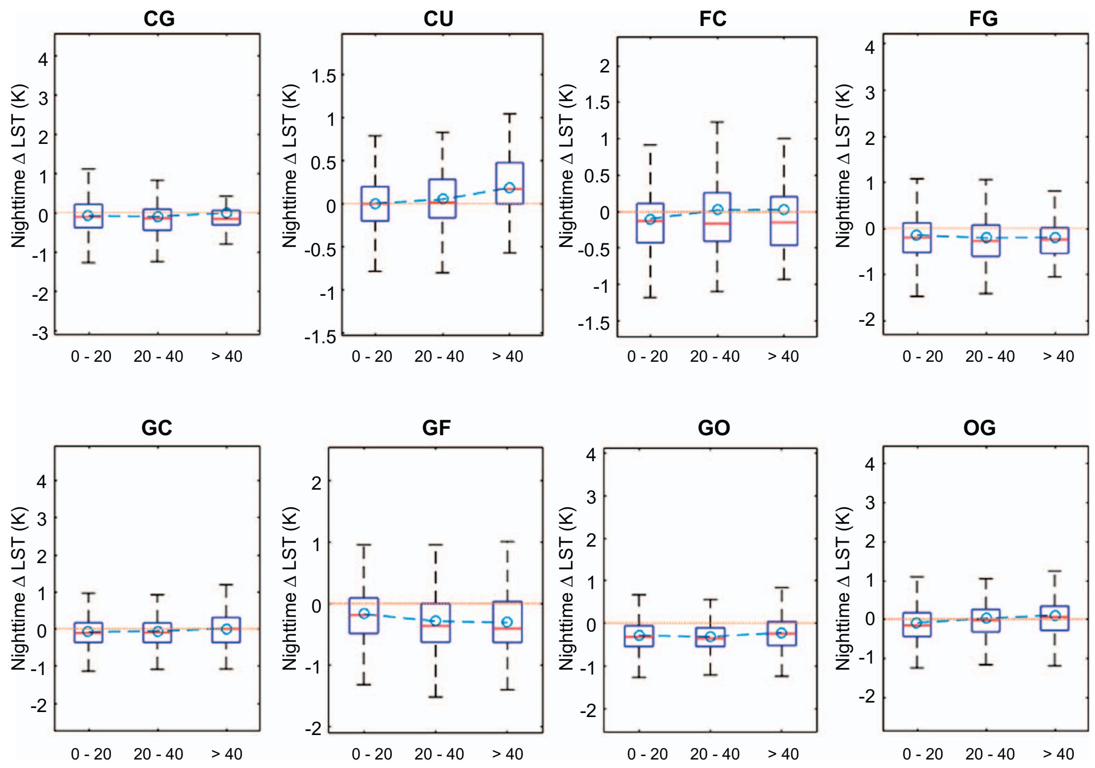

Figure 4. Boxplots of annual mean changes in nighttime LST (K) during 2001–2012 for different land cover transition (%) bins due to each type of land cover transitions in China. For each box, the central red mark is the median, the edges of the box are the 25th (Q1) and 75th (Q3) percentiles, and the whiskers extend from the lowest value within the lower limit (Q1−1.5 (Q3–Q1)), to the highest value within the upper limit (Q3+1.5 (Q3–Q1)). The blue circle represents the average values of nighttime LST change for different land cover transition bins.

Annual daytime ΔLSTs caused by land cover transitions were found significantly and negatively correlated with ΔET and ΔAlbedo. Some previous studies also showed negative relationships between ET and LST, such as under the energy-limited or water-limited conditions, or when LST was above a certain value(Cao and Gao 2013, Xiong *et al* 2016). The correlations between nighttime ΔLST and ΔET (or ΔAlbedo) were negative for some transitions but positive for others (figure 5). It is also found that ΔET and ΔAlbedo were correlated more strongly with daytime ΔLST than with nighttime ΔLST, similar to previous findings (Zhao *et al* 2017, Sun and Kafatos 2007). Daytime ΔLST caused by FC was significantly and negatively correlated with ΔAlbedo, which indicates the cooling effects of FC might be controlled by an increase in albedo. The decreases in both daytime and nighttime LSTs caused by GF were associated most strongly with the increase in ET (figure 5). Further investigation suggested that ΔLST is controlled primarily by ΔAlbedo in cold months (March, November, and December), and by ΔET in warm months (August and September) (figure S2). However, similar seasonal sensitivities of nighttime ΔLST to ΔET were not found.

The correlations mentioned above (figure 5) indicate that ΔET and ΔAlbedo caused by land cover transitions might control ΔLST, and the results presented in figure 6 and figure 7 confirm this hypothesis. The impact of ΔAlbedo caused by FC on daytime ΔLST was reasonably significant, with an increase in albedo leading to a cooling effect on LST during daytime, and the contribution of ΔAlbedo to daytime ΔLST was >50% (figure 3, figure 5, and figure 7). Unger (2014) also reported that conversions from forest to cropland resulted in enhanced surface albedo and decreased surface net radiation, and that biogenic volatile organic compound emissions and atmospheric chemistry imposed an additional radiative cooling effect, comparable with that of surface albedo changes. We found a cooling effect of FC during nighttime, but a slight warming effect if we considered only those pixels with transition amounts >40%. This might indicate the uncertainties of nighttime ΔLST caused by FC. Additionally, this phenomenon could be explained as nighttime warming reflecting the release of daytime heat storage, as verified by the observed phenomenon that the nighttime ΔLST over FC regions was dominated by ΔET rather than by ΔAlbedo, especially at the higher quantiles of changes in nighttime LST, as shown in figure 6 and figure 7 (Zhou *et al* 2016, Peng *et al* 2014).

The GF transition cooled LST because of enhanced ET (figure 5 and figure 7), which agrees with the results of Peng *et al* (2014). Moreover, we showed GF continued to cool LST at night, which could be attributed largely to the increase in ET. The impact of ΔET on the higher quantiles of ΔLST was more significant than on the lower quantiles (figure 6). Similar to previous

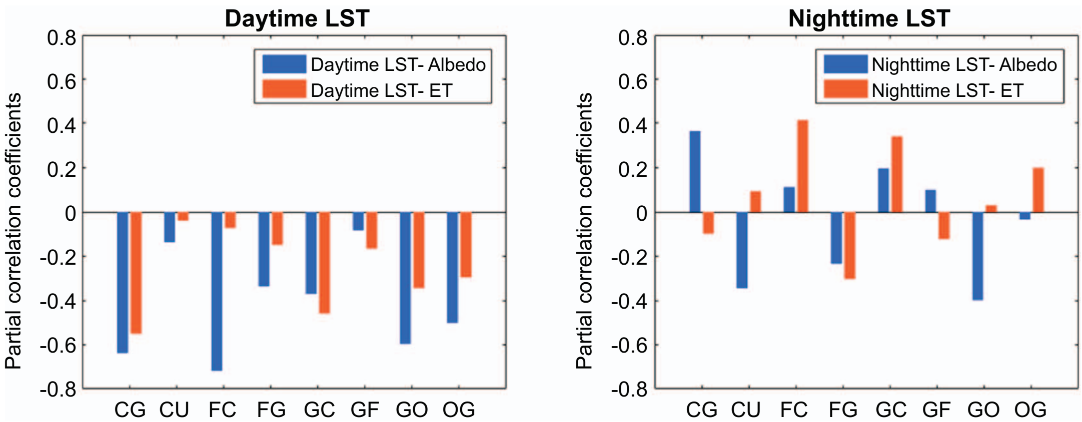

Figure 5. Partial correlations of annual daytime ΔLST with ΔET and ΔAlbedo, and annual nighttime ΔLST with ΔET and ΔAlbedo during 2001–2012 over each land cover transition area with transition amounts >40%.

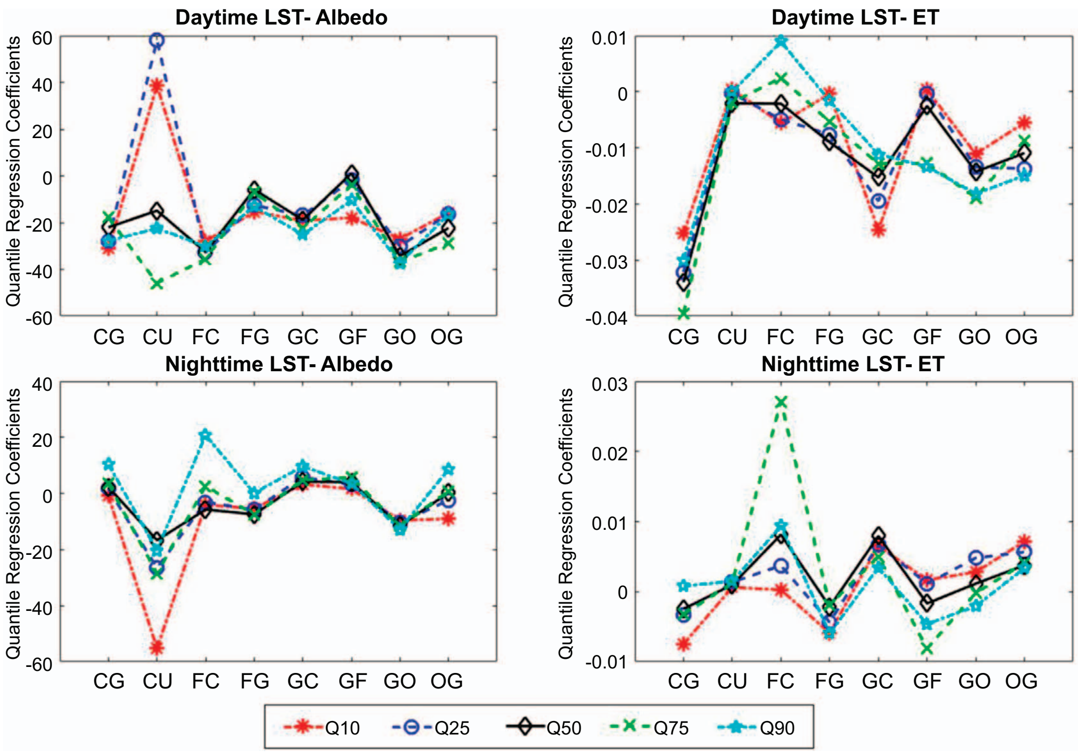

Figure 6. Quantile regression of changes in daytime LST with albedo change, and ET change, and changes in nighttime LST with albedo change, and ET change at the 10th, 25th, 50th, 75th, and 90th percentiles for land cover transition areas with transition amounts >40%.

findings (Hu *et al* 2015), the warming effect on LST due to CU was clearly larger during daytime compared with nighttime. The contributions of ΔET and ΔAlbedo to ΔLST were relatively limited (figure 7), which indicates the dominant mechanisms of the warming effect of urbanization in China might be other factors, such as large-scale climate variability or greenhouse gases (Zhao *et al* 2014, Sun *et al* 2016, Shi *et al* 2014), rather than ET and albedo.

Generally, changes in albedo and ET due to different land cover transitions contributed to <60% of daytime ΔLST, and the predominant biophysical effects on daytime ΔLST were manifest through changes in surface albedo instead of ET (figure 7). Among the major land cover transitions considered in this study, the climatic effects of albedo change due to FC transition were larger than other transitions at the annual timescale, while the climatic effects of ET change due to GC transition were larger than other transitions during the day.

3.3. Implications and uncertainties

Previous studies have concentrated primarily on the climatic effects of one individual LULCC type or they have considered all LULCC types together without distinction. This has been improved in recent studies by

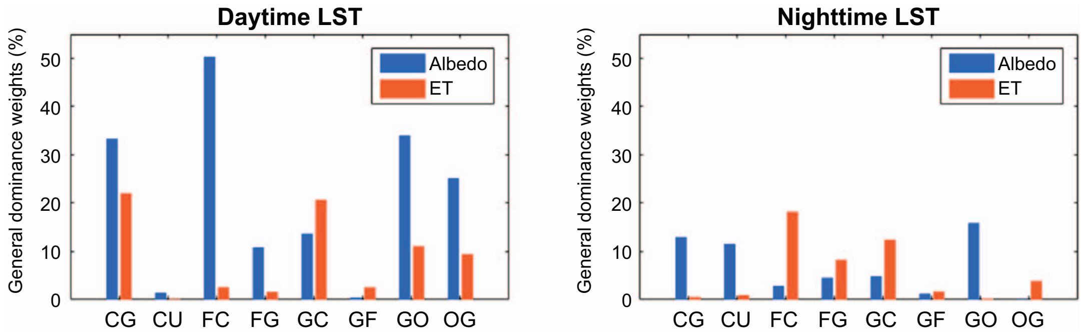

Figure 7. Contributions of albedo change and ET change to daytime ΔLST and nighttime ΔLST for land cover transition areas with transition amounts >40%.

considering the climatic effects of two or more types of LULCC (Shi *et al* 2014, Zhou *et al* 2016). Here we considered all major land cover transition types in China and investigated their individual climatic effects. Results suggested a warming effect on LST associated with CU transition, while FC and GF transitions produced cooling effects but with different dominant mechanisms. Surface albedo played an important role in the cooling of LST in FC regions, and ΔET was the primary controlling factor in GF regions. This highlights the necessity to consider the individual climatic effects of different land cover transitions or conversions in climate research studies.

It should be noted that uncertainties exist in this analysis because of data and technical limitations. The temporal mismatch between land cover transition (1990–2005) and change in satellite observations (ET, albedo, and LST, available since 2000) could have introduced uncertainties that might have led to further misinterpretation of the biophysical factors that control ΔLST. To exclude this possibility, we derived land cover transitions during 1990–2000 and 2000–2005, and quantified the associated changes in annual LST, ET, and albedo during both 2001–2012 and 2001–2006. We then explored the relationship between ΔLST and changes in the biophysical variables (ET, albedo) during 2001–2006 and the changes associated with transitions during 2000–2005, and that during 2001–2012 and 1990–2000, respectively. The former had a good match between land cover transition and changes in LST, ET, and albedo, and it should represent the temperature changes caused by land cover transitions, while the latter described the short-term changes in LST, ET, and albedo after land cover transitions. Similar results were obtained regarding the impacts of land cover conversions on surface temperature and on how land cover conversions affect LST through modification of ET and albedo, which were consistent with the results of this study. This indicates the independence of our results in relation to the period of land cover transitions and LST data used. Furthermore, it provides additional information indicating that the climatic effects of land cover transitions could persist for several years (Zhang and Liang 2014).

We attempted to minimize the effects of background climate by removing the average anomalies of all the pixels in each climate zone that might introduce uncertainties. To investigate the sensitivity of our results to the inferred reference temperature, two alternative references were used to quantify the changes in LST, ET, and albedo due to land cover transitions, but no significant differences were found (supplementary figure S1). In order to reduce the influences of elevation and geographical location, previous studies have used planar surface models (Zhou *et al* 2016, Li *et al* 2015) to estimate the spatially distributed reference temperature, and performed an elevation adjustment by subtracting the elevation-induced ΔLST from the original value. In this study, we also explored the impact of elevation on the ΔLST but found no significant correlation between them. In summary, our results should be sufficiently robust to provide observational evidence of the climatic effects of multiple land cover transitions and to show how they affect LST through modification of surface albedo and ET, despite the existence of uncertainties.

4. Conclusions

To the best of our knowledge, this research was the first to quantify the impacts of diverse land cover transitions on surface temperature using satellite data. It offered an initial examination of the extent to which land cover transitions influence surface climate, revealed how they might affect climate change through modification of albedo and ET, and examined whether different land transition types produce diverse climatic impacts. Results showed a warming effect on LST by the transition from cropland to urban land use, and a significant cooling effect on LST by the expansion of cropland from forest and by afforestation of former grassland areas, but via different physical mechanisms. The transition from forest to cropland decreased daytime LST primarily because of the increase in surface albedo, while a decrease in LST caused by afforestation of grassland was primarily because of enhanced ET. This highlights the necessity to consider the individual climatic effects of different land cover transitions or conversions in climate research studies.

This short-term analysis of land cover transitions in China means our estimates should represent local temperature effects. Moreover, local or regional temperature could be affected by other factors, since the changes in ET and albedo explained <60% of the total variance. Additional factors (e.g. changes in emissivity, redistribution of sensible and latent heat, and emissions of carbon dioxide and biogenic volatile organic compounds) could be considered in future studies to provide more robust conclusions concerning the climatic impacts of LULCC (Unger 2014, Zhao and Jackson 2014, Juang *et al* 2007). Furthermore, climate models might be used to support our observational evidence and provide supplementary information in the future.

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