Does urbanization increase diurnal land surface temperature variation? Evidence and implications

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HIGHLIGHTS

• Satellite images were used for landscape changes assessment in Taipei.
• Policies on urban development can quickly affect landscape changes in Taipei.
• Urbanization increases urban diurnal land surface temperature variation.
• Urbanization results in a greater increase in urban heat absorption than in thermal inertia.

ABSTRACT

The diurnal land surface temperature (LST) variation is a primary characteristic of the effects of urbanization. However, no study to date has focused on changes in diurnal LST variation in urban environments. This paper investigates the effects of urbanization on landscape pattern and diurnal LST variation of Taipei City, using MODIS thermal images and SPOT multispectral remote sensing images over the 1994–2010 period. Supervised land-cover classifications were conducted to investigate decadal land-cover changes within the study area. A remote-sensing-based urbanization index was adopted as a quantitative measure of urbanization-induced changes in landscape patterns. Diurnal LST variations were assessed using MODIS Aqua satellite images. We found that the diurnal LST variation increases with the urbanization index, with the adverse effects of urbanization on the diurnal LST variation being more substantial in the earlier stages of urbanization. Increasing diurnal LST variation due to urbanization implies that urbanization is likely to result in a greater increase in urban heat absorption than in thermal inertia. This research provides insightful supporting evidence that, in mitigating UHI effects, measures that can reduce urban heat absorption such as urban parks, community green spaces, green roofs and cool (or permeable) pavements should be given higher priority.

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1. Introduction

Urbanization typically results in built-up environments containing large areas of impervious surfaces with increased thermal inertia. Urbanization impacts stormwater runoff, air quality and carbon concentration (American Forests, 2005), net primary productivity and soil respiration rates (Kaye, McCulley, & Burke, 2005), and ambient air temperatures (Cheng, Su, Kuo, Hung, & Chiang, 2008). Researchers have developed different landscape metrics for quantitatively evaluating the effects of urbanization including changes in land-cover patterns, impacts on urban ecosystems, and deterioration of urban air quality (O’Neill et al., 1988; Plotnick, Gardner, & O’Neill, 1993; Riitters et al., 1995; Riitters, O’Neill, Wickham, & Jones, 1996). Several studies have also demonstrated that such landscape metrics can be derived using remote sensing images (Deng, Wang, Hong, & Qi, 2009; Griffith, Stehman, Sohl, & Loveland, 2003; Herold, Scepan, & Clarke, 2002). Most of such landscape metrics have been used to characterize changes in land-cover patterns and their effects on environmental and ecological regularities within a region. Frohn and Hao (2006) suggested that spatial
resolution should be considered when applying metrics to quantify the spatial patterns of landscapes. Li, Zhou, and Ouyang (2013) showed that LST was negatively correlated with the percentage of green space cover in Beijing; however, the relationship varied depending on spatial resolution. Sun, Wu, Lv, Yao, and Wei (2013) demonstrated that landscape-level metrics could identify different types of urban growth in the city of Guangzhou, China.

Although numerous landscape metrics have been proposed, only a few of such metrics are suited to quantify the degree of urbanization. The most apparent characteristic of urbanization is the increase of built-up land cover. Therefore, the percentage of apartment buildings in total construction housing (Kouichi, 1987), road density and percentage of built-up area (Lee, Ding, Hsu, & Geng, 2004), and the proportion of impervious surfaces (Yuan & Bauer, 2007) were conveniently used as urbanization indices. However, modern urban planning often requires the establishment of large green spaces to alleviate the adverse effects of urbanization such as an increase in the ambient air temperature and deterioration of urban air quality. To reflect the effects of urban green spaces, a remote-sensing-based urbanization index that integrates the normalized difference vegetation index (NDVI) and coverage ratio of built-up land cover was developed and used to assess the degree of urbanization in different Asian cities (Guo, Wang, Cheng, & Shu, 2012; Hung, Chen, & Cheng, 2010).

One of the major concerns related to urbanization is its effect on the urban thermal environment. Atmospheric heat islands are normally measured by in situ air temperature sensors; by contrast, a surface urban heat island (SUHI) refers to the excess warmth of urban areas compared with the non-urbanized surroundings, and it is measured using LST levels observed by thermal infrared remote sensing (Yuan & Bauer, 2007). Voogt and Oke (2003) concluded that NDVI-based metrics are favorable for describing the differences between urban and rural surface properties. Oke, Johnson, Steyn, and Watson (1991) addressed the roles of surface geometry and surface thermal properties in the creation of SUHIs and the importance of assessing these parameters in both urban and rural environments.

The intensity of the UHI effect is often measured as the difference between the temperature found in the center of an urban area and the background rural temperature (Atkinson, 2003; Hung, Uchihama, Ochi, & Yasuoka, 2006). The thermal inertia estimated using remote sensing thermal images has also been used in studies related to UHI effects (Chen, Du, & Dong, 2008; Nasipuria, Majumdar, & Mitra, 2006). The estimation of the thermal inertia of an earth surface object is dependent on two factors: the albedo and diurnal LST variation (Nasipuria et al., 2006). The apparent thermal inertia (ATI) is a measure of the proportion of radiation absorbed, divided by the subsequent increase in surface temperature (ΔT):

$$\text{ATI} = \frac{NC(1 - \alpha)}{\Delta T}$$  

(1)

where $N$ is the scaling factor, $C$ is a constant determined by the latitude and solar declination angle, and $\alpha$ is the apparent albedo (Nasipuria et al., 2006). Therefore, the diurnal temperature variation in an object is dependent on its absorbed energy [i.e., $NC(1 - \alpha)$] and apparent thermal inertia. Objects possessing low thermal inertia and albedo (and, by implication, high absorptance) display considerable diurnal temperature variation. Both thermal inertia and albedo vary depending on the type of land cover, and therefore changes in land cover caused by urbanization have a direct impact on the diurnal temperature variation in an urban environment. Hence, the variation in diurnal LST is a primary characteristic of the effects of urbanization.

In contrast to the UHI effect, few studies have focused on diurnal temperature variations in urban environments (Argüeso, Evans, Fita, & Bormann, 2014; Georgescu, Moustaoui, Mahalov, & Dudhia, 2011; Qiao, Tian, & Xiao, 2013; Wouters, De Ridder, Demuzere, Lauwaet, & Van Lipzig, 2013). Patterns of land-cover change, including the composition of vegetation, water, and built-up, are complicated, and characterizing how they are linked with changes in diurnal LST variation is difficult. For example, the instantaneous field of view of most space-borne thermal sensors covers a substantial mix of surface elements. Therefore, the effect of urbanization on diurnal LST variation is scale-dependent and involves a certain degree of uncertainty because of the combined effect of different land-cover types within the spatial scale of interest. In addition, most studies on urban temperature environments have focused on air temperatures or UHI effects (Argüeso et al., 2014; Qiao et al., 2013; Qu, Wan, & Hao, 2014). Nevertheless, it is still unclear how urbanization-induced landscape changes affect diurnal LST variation and what such changes in urban diurnal LST variation imply. To the best of our knowledge, no study to date has focused on changes in diurnal LST variation in urban environments. Therefore, the objectives of the current study were threefold: (1) to quantitatively investigate landscape changes in the study area by using a remote-sensing-based urbanization index; (2) to assess the effect of urbanization on diurnal LST variation and investigate its implications; and (3) to evaluate the effectiveness of the urbanization index in characterizing such effects, taking into account possible uncertainties.

2. Methodology

2.1. Study area and data

Fig. 1 shows the analytical framework of this study. A portion of the Taipei Metropolitan Area (Fig. 2) comprising the old city center in the west (Region A), a region of early expansion in the center (Region B), and a newly developed industrial-business-residential complex region in the east (Region C) was selected for this study. Fig. 2 also shows three subregions ($S_1$, $S_2$, and $S_3$) selected to demonstrate changes in landscape patterns (Section 4). The Keelung River, one of the major rivers of northern Taiwan, flows through the study area from the central-east region to the northwest corner.

Six sets of SPOT satellite multispectral images of the study area over the 1994–2010 period were collected from a receiving station located at the Center for Space and Remote Sensing Research at National Central University in Taoyuan, Taiwan. The digital-number vectors of individual pixels of the SPOT multispectral images are linearly related with the total radiance, including solar radiances reflected from the surface of the earth and solar radiances scattered by the atmosphere, measured by the sensors onboard the satellite. MODIS images were also obtained from the website of NASA’s Earth Observing System Data and Information System to determine daytime and nighttime LSTs under clear-sky conditions at a spatial resolution of 1 km. Table 1 summarizes the properties of these images and other relevant information. In addition to the SPOT and MODIS satellite images, historical records of major policies and stages of urban development in Taipei were acquired, mostly from official documents. All satellite images were georeferenced using a set of ground control points. Digital numbers obtained from the raw SPOT images were firstly converted to at-sensor radiances by using the offset and gain values of the detectors. Atmospheric correction was then applied using the dark-object subtraction (DOS) method (Chavez, 1975; Cheng & Lei, 2001; Cheng, Su, Yeh, Chang, & Hung, 2012; Schott, 1997). The basic concept of the DOS method is to identify particularly dark features within the scene. On the basis of the principles of remote sensing, large and clear water bodies and shadows cast by clouds or large topographic features have radiances at zero or nearly zero, because...
Data acquisition and preprocessing

- Selecting the study area and identifying subregions of different urban expansion periods.
- Collecting SPOT & MODIS LST images & historic records of major policies and urban developments in Taipei.
- Preprocessing (georeferenced and atmospheric correction) of SPOT images.

Analytical procedures

- Determining major land-cover types in the study area (Built-up, woods, grass/crop, & Water bodies).
- LULC classification using SPOT multispectral images.
- Calculating pixel-NDVI values from SPOT multispectral images.
- Calculating cell-average NDVIs & cell-based urbanization index.
- Calculating diurnal LST differences from MODIS LST images.

Results evaluation

- Quantifying landscape changes by urbanization indices.
- Investigating the relationship between the urbanization index and diurnal LST difference.
- Assessing changes in diurnal LST difference due to urbanization.

Results evaluation

- Calculating diurnal LST differences from MODIS LST images.

Fig. 1. Analytical framework of this study.

Fig. 2. False-color SPOT satellite image (acquired in 2010) of the study area. Regions A, B, and C are the old city center, early-expansion region, and newly developed region, respectively.

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<th>Table 1</th>
<th>Properties and related information of the satellite data used in this study.</th>
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<td></td>
<td>Acquisition dates</td>
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<tr>
<td>SPOT multispectral images</td>
<td>09/09/1994 07/16/1998 07/01/2000 07/12/2004 08/28/2007 08/02/2010</td>
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<tr>
<td>MODIS LST images</td>
<td>07/21/2004 08/08/2004 08/16/2004 09/30/2004 07/21/2007 09/14/2007 07/04/2010 07/18/2010 09/08/2010 09/22/2010</td>
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clear water exhibits strong absorption in the near-infrared spectrum and little radiance is scattered to the sensor from shadowed areas. However, because of significant atmospheric scattering, analysts often find that the lowest radiances are not at or near zero, but some higher values. The higher values of the lowest radiances are mainly caused by the atmospheric scattering effect. Therefore, the effect of atmospheric scattering can be roughly eliminated by subtracting the lowest radiances of individual spectral channels from the at-sensor radiances, and the resultant radiances are considered representative of those leaving the surface of the Earth.

Ten sets of MODIS images acquired in 2004, 2007, and 2010 during the hot season (July to September) were used to investigate the diurnal LST variation within the study area. The MODIS LST was derived from two corrected thermal bands in the 10.5–12.5 μm spectra by using the split-window LST algorithm with a reported accuracy of 1° K (Hung et al., 2006).

2.2. Land-use/land-cover classification

Changes in land-cover types are a direct consequence of urbanization. Because urban landscapes are typically characterized by parcels or patches of unique land-cover types, patch- or cell-based (instead of pixel-based) approaches are commonly adopted in studies of urban ecology and urban planning. For example, Hung et al. (2010) developed a remote-sensing-based urbanization index that integrates the coverage ratio of the built-up land cover and mean NDVI within a cell of 1 km × 1 km coverage.

To assess land-cover changes in the study area, a land-use/land-cover (LULC) classification was applied to each set of SPOT multispectral images. Four land-cover classes, namely woods, grass/crops, built-up areas, and water bodies, were used for the classification. Bare land parcels under public-works construction display spectral reflectance patterns that are similar to those of other types of built-up land cover. In our study area, most bare land parcels were construction sites and thus were technically considered to be part of the built-up land-cover class.

The radiances of the green, red, and near-infrared channels were used as the classification features after atmospheric correction. We adopted the supervised Bayes classification, which assumes a multivariate Gaussian distribution for the classification features. Schowengerdt (1997) and Schott (1997) have provided detailed explanations of the supervised classification and the Bayes classification method, which is briefly described as follows.

Let \( C_i (i = 1, \ldots, M) \) represent the different land-cover classes that are present in a study area and \( X^T = (X_1X_2 \cdots X_n) \) represent a set of \( n \) classification features characterizing different land-cover classes. Assume that these features form a multivariate Gaussian distribution with the mean vector \( \mu \) and covariance matrix \( \Sigma \) defined as

\[
\mu = [\mu_1 \cdots \mu_n]
\]

\[
\Sigma = \begin{bmatrix}
\sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\
\sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn}
\end{bmatrix}
\]

where \( \mu_i \) represents the mean of the feature \( X_i \) and \( \sigma_{ij} \) represents the covariance between features \( X_i \) and \( X_j \). The Bayes classification method takes into account the a priori probabilities of individual land-cover classes (i.e., \( p_i, i = 1, \ldots, M \)) in the study area. A pixel with feature vector \( X \) is assigned to \( C_i \) if the a posteriori probability that the pixel belongs to \( C_i \) (namely, \( p(C_i|X) \)) is maximal:

\[
p(C_i|X) > p(C_j|X), \quad j \notin \{1, 2, \ldots, M; j \neq i\}.
\]

The preceding decision criterion is equivalent to assigning the pixel to \( C_i \) if

\[
d_i(X) > d_j(X), \quad j \in \{1, 2, \ldots, M; j \neq i\}
\]

with the discriminant function defined as

\[
d_i(X) = \ln p_i - \frac{1}{2} \ln \left| \Sigma \right| - \frac{1}{2} (X - \mu_i)^T \Sigma^{-1} (X - \mu_i), \quad k = 1, 2, \ldots, M.
\]

In Eq. (6), \( \mu_k \) and \( \Sigma_k \) represent the mean vector and covariance matrix of \( X^T = (X_1X_2 \cdots X_n) \) for Class-\( k \), respectively.

Implementing the supervised land-cover classification by using remote sensing images generally involves the following steps (Cheng et al., 2008):

1. Identifying the land-cover classes.
2. Determining the classification features.
3. Collecting training pixels of individual land-cover classes. This is accomplished through field investigations and by referencing aerial photos to identify areas on satellite images that are representative of different land-cover classes.
4. The decision rules previously described are used for assigning unknown pixels to land-cover classes with the maximum a posteriori probabilities.

2.3. Cell-based urbanization index

In addition to the LULC classification, the NDVI values of individual pixels (\( NDVIp_{\text{pixel}} \)) were calculated using the radiances of the red and near-infrared channels (Hung et al., 2010):

\[
NDVIp_{\text{pixel}} = \frac{I_{\text{IR}} - I_{\text{IR, min}}}{I_{\text{IR}} - I_{\text{IR, min}}} + \frac{I_{\text{R}} - I_{\text{R, min}}}{I_{\text{R}} - I_{\text{R, min}}}
\]

where \( I_{\text{IR}} \) and \( I_{\text{R}} \) are the at-sensor radiances of the near-infrared and red channels, respectively; \( I_{\text{IR, min}} \) and \( I_{\text{R, min}} \) are the corresponding minimum radiances within individual scenes. By subtracting the minimum radiances of the red and near-infrared channels from the at-sensor radiances, the NDVI values calculated using Eq. (7) can be considered as those at the top-of-canopy level, according to the concept of the DOS method for atmospheric correction. Hung et al. (2010) demonstrated that cells dominated by built-up land cover tend to have negative cell-average NDVI values, and, by contrast, cells dominated by grass/crops or woods are associated with positive NDVI values. Hence, the cell-average NDVI plays an essential role in quantifying the effects of urbanization.

The cell-based urbanization index \( U_{\text{cell}} \) (Hung et al., 2010) can be calculated as follows:

\[
U_{\text{cell}} = p_b(1 - NDVIp_{\text{cell}})
\]

where \( p_b \) represents the coverage ratio of the built-up land-cover type within the 1 km × 1 km spatial coverage of individual cells and \( NDVIp_{\text{cell}} \) is the cell-average NDVI. Cell-specific \( p_b \) values were calculated on the basis of the LULC classification results. Higher \( U_{\text{cell}} \) values indicate more significant urbanization effects.

2.4. Diurnal LST temperature variation

In this study, the effect of urbanization on diurnal LST variation was assessed by investigating the relationship between the cell-average urbanization index and diurnal LST variation derived from MODIS images. Both parameters were measured at a spatial scale of 1 km × 1 km. Only cloud-free pixels from the MODIS images were used to calculate the diurnal LST variation in this study.

Fig. 3 illustrates the diurnal cycle of summer time 2-m air temperatures in Taipei. The highest and lowest air temperatures mainly
occurred at 1:00 p.m. and 5:00 a.m. local time, respectively. The daytime acquisition time for MODIS images (approximately 1:00 p.m. local time) coincides with the hour of the highest air temperature, and the nighttime acquisition time (2:00 a.m. local time) occurs 3 h before the hour of lowest air temperature. However, the temperature gradient before dawn is relatively low and the difference between the average air temperatures at 2:00 a.m. and 5:00 a.m. is 0.57° C in Taipei. Assuming a similar pattern for the diurnal cycle of land surface temperatures, the MODIS LST images can be used to assess the effects of urbanization on the diurnal LST variation, although the estimates made with MODIS LST images are likely to be conservative.

3. Results

The confusion matrices of the LULC classification results established on the basis of selected training pixels are summarized in Table 2. Most of the classification accuracy rates were higher than 80%, with those of the built-up and water body classes exceeding 90%. The grass/crop class had lower accuracies, and the woods and the grass/crops were the most likely to be mistaken for each other because of their similar spectral response patterns. The empirical probability density functions of the pixel-NDVI values (NDVIpixel) of different LULC classes are shown in Fig. 4. The woods and grass/crop classes demonstrated positive pixel-NDVI values, whereas most pixels of the built-up and water classes exhibited negative pixel-NDVI values. The average NDVIpixel values of the built-up, woods, water, and grass/crops were −0.008, 0.711, −0.223, and 0.379, respectively.

Fig. 5 illustrates the spatial variations of the LULC classes and UIcell during 1994–2010. In general, the UIcell values were highest in Region A (the old city center) in the west and lowest in Region C (the newly developed region) in the east. According to the decadal variations of the LULC classes and UIcell values in Fig. 5, most significant land-cover changes occurred in S1, S2, and S3. Such changes resulted from several major projects and policies that were implemented in Taipei over the period of 1991–2010. The details of these projects and policies and discussions of how they affected landscape patterns and UIcell values within these subregions are described in Section 4.1. The empirical cumulative distribution functions (ECDF) of UIcell over the same period are also shown in Fig. 6. In general, the degree of urbanization in the study area decreased during 1994–2007 and increased slightly in 2010 because of developments in several of the subregions (Section 4).

Fig. 7 presents scatter plots of the diurnal LST variation (ΔLST) versus cell-average urbanization indices in July, August, and September. The diurnal LST variation largely varied from 5 to 20° C. Regardless of the significant uncertainties, the scatter plots of individual months (Fig. 7(a)–(c)) demonstrate an increasing trend in the diurnal LST variation with an increase in the urbanization index. Fig. 7(d) shows the average ΔLST–UIcell relationships of individual months determined using UIcell values in the ranges of (0, 0.3), (0.3, 0.5), (0.5, 0.7), and (0.7, 1.0). Vertical bars represent the range of one standard deviation from the average ΔLST. The standard deviation of ΔLST varied from approximately 3.5° C for UIcell values lower than 0.07 to approximately 2.5° C for UIcell values higher than 0.6. The average ΔLST–UIcell relationships shown in Fig. 7(d) indicate that, at a 1-km spatial resolution, the cell-average urbanization index can quantify the average effect of urbanization on the diurnal LST variation. With the estimated standard deviations of ΔLST ranging from 2.5 to 3.5° C for various values of UIcell, it is reasonable to report that the ΔLST–UIcell relationships can provide estimates of ΔLST with a standard error of approximately 2.5–3.5° C.

The preceding results indicate that, on average, the diurnal LST variation increased with urbanization. Previous studies (Qu et al., 2014; Wouters et al., 2013) have found that, compared with rural areas, urban areas have lower rates of diurnal air temperature variations. Our study shows that changes in diurnal LST variation differ from those in diurnal air temperature variation. The average ΔLST for higher UIcell values in July and August was approximately 15° C. The average summertime diurnal LST variation of built-up land in Beijing was reported to be approximately 12° C (Qiao et al., 2013). Kuttler (2012, Chapter 6) revealed that different types of roofing displayed substantially different diurnal LST variation during clear and calm weather in summer, ranging from 10 to 12° C for watered and planted roofs to 25–35° C for roofs covered in bright gravel or paint. In addition, Zhan et al. (2012) found that the diurnal LST variation in an urban environment varied considerably, ranging from approximately 12° C for shaded ground to 40° C for roofs. Comparing with these diurnal LST variations, we conclude that the average ΔLST values and associated standard
deviations observed in our study are highly reasonable. The heterogeneities in land-cover types and their compositions and the structural variability of landscape (in terms of structure geometry and density of urban surface features) within the 1 km × 1 km coverage of each cell may have contributed to uncertainties in the diurnal LST variation, as explained in Section 4.

4. Discussion

4.1. Quantifying landscape changes by urbanization indices

Beginning in 1991, several major projects and policies having profound effects on landscape patterns in Taipei were implemented. Such projects and policies are summarized as follows:

(1) Channelization of the Keelung River

The Keelung River, one of the major rivers of northern Taiwan, flows through the northern part of Taipei. The Taipei City Government and the Water Resources Agency (WRA) of Taiwan started the Keelung River Channelization Project (KRCP) in November 1991. Engineering projects within the water course were largely completed by November 1993. The newly gained land parcels, located mostly within S2 and S3, were gradually developed into riverine parks, industrial complexes, shopping malls, and residential areas in subsequent years.

(2) Implementation of the Taipei Healthy City Initiative (THCI)

Responding to the Healthy Cities movement of the World Health Organization (WHO), the Taipei City Government announced the Taipei Healthy City Initiative in 2002. The WHO adopted 32 indices for assessing the health status of a city. Among these indices, the percentage of green space and the green space area per person are directly related to LULC conditions. A major goal of the THCI was to increase the percentage of green space (including neighborhood green space or parks, trees on sidewalks, and riverine parks). With this initiative, the Taipei City Government provided incentives to transform privately owned unused open spaces into neighborhood green spaces or parks, in an effort to improve the air quality and livability of the city. With such incentives, many unused lots, most
of which had impervious surfaces, were turned into green spaces or neighborhood parks.

(3) Organizing and hosting the 2010 Taipei International Flora Exposition (TIFE)

The TIFE opened in November 2010 and ran until April 2011. The expo was held within S1 and the area has since become the Taipei Expo Park.

Fig. 8 demonstrates details of the LULC changes within S1, S2, and S3 from 1994 to 2010. In 1994, the land parcels newly gained because of the KRCP within S2 and S3 were generally bare land parcels under public works construction, and several old river reaches were still present. Revegetation plans were then implemented within S2 and S3, resulting in considerable increases in riverine parks and green spaces during 1994–1998. In 2002, the Neihu Science Park (NSP) development plan was launched in S2 and S3. Several phases of land-use deregulation plans went into effect in 2002, 2008, and 2011, allowing for the construction of R&D complexes, shopping malls, and entrepreneur headquarters in the NSP territory, respectively (DOED-TPE, 2014).

The implementation of the THCI resulted in a considerable increase in green spaces around the city. Over 20ha of neighborhood green spaces had been established by 2010 (DOUD-TPE, 2014). The combined effects of the mentioned projects and policies engendered an overall drop in the urbanization indices from 1994 to 2007 (Fig. 6). By 2010, S2 and S3 had undergone accelerated development, achieving higher UIcell values. In addition, although TIFE attempted to emphasize the development of more urban green spaces, impervious facilities such as exhibition domes, pavilions, food courts, and walkways were built within S1, replacing the original green spaces (Fig. 8). Therefore, the urbanization index demonstrated a slight increase in 2010.

Although urbanization indices generally decreased during 1994–2007, changes in the urbanization indices of S2 and S3 were not consistent with the overall pattern. Fig. 9 illustrates tempo-
The preceding analyses demonstrate that, at least for a mid-sized city like Taipei, decisions and policies on urban development can have a relatively quick effect on landscape patterns. Notably, developments in S2 and S3 have accelerated in recent years, possibly because of the land-use deregulation plan effective from 2008. Although the deregulation of land use for industrial development in the NSP has contributed a significant revenue increase for the city in recent years, it has also resulted in higher degrees of urbanization, which in turn has had adverse environmental effects, as presented in the following section.

4.2. Assessing changes in diurnal land surface temperature variation due to urbanization

Urbanization refers to the process of increasing impervious surfaces that have higher thermal inertia than surfaces with vegetation and water bodies. Within an urban environment, the average thermal inertia increases with the proportion of impervious areas and construction materials such as concrete and asphalt. The anthropogenic heat release stemming from energy consumption by industrial processes, buildings, vehicles, and human metabolism can further elevate the UHI effects (Sailor, 2011; Yuan & Bauer, 2007). In addition, an urban canopy is characterized by complex factors including the building materials, structural geometry, and density of urban surface features (Atkinson, 2003; Voogt & Oke, 2003). The combined effect of these factors typically causes the longwave radiation released by urban land surfaces and the anthropogenic heat release to be trapped by blocks of tall buildings, which in turn results in increasing heat absorption by the urban environment. Eq. (1) indicates that the diurnal LST variation ($\Delta$LST) is the ratio of the heat energy absorbed by objects on land surfaces to their apparent thermal inertia. In a complex urban environment involving various proportions of different types of land cover and
Fig. 8. LULC of S1, S2, and S3 during 1994–2010.
urban structural geometry, the apparent thermal inertia and heat energy absorption can vary in degree from one location to another, in addition to being dependent on the spatial scale of interest.

Uncertainties in the \( \Delta LST - UI_{cell} \) relationship, as demonstrated in Fig. 7, can be attributed to several factors. First, within the spatial coverage of a 1 km \( \times \) 1 km cell, different combinations of LULC types may result in the same \( UI_{cell} \) values, whereas their effects on the diurnal LST variation may differ significantly. Spatial green space patterns, both composition and configuration, were also found to considerably affect LSTs (Li et al., 2013). Environmental factors and plant-specific thermal and optical characteristics can also contribute to uncertainties in LST changes (Feyisa, Dons, & Meilby, 2014). In addition, the diurnal LST variation itself is positively correlated to the highest daytime temperature. Therefore, natural variation in daytime temperatures also contributes to uncertainties in the variation of diurnal LSTs. Reducing the spatial coverage of cells for \( \Delta LST \) and \( UI_{cell} \) calculations by using finer resolution thermal images (such as ASTER thermal images with 90-m resolution) may facilitate reducing the within-cell heterogeneity of land-cover types and landscape structural variability, thus lowering the uncertainties of the \( \Delta LST - UI_{cell} \) relationship.

Fig. 7(d) demonstrates a more evident relationship between the average diurnal LST variation and the average \( UI_{cell} \). The diurnal LST variation in September was lower than that in July and August because of lower daytime temperatures. Changes in the diurnal LST variation were also greater for lower \( UI_{cell} \) values (\( UI_{cell} < 0.4 \)). By contrast, for higher \( UI_{cell} \) values (\( UI_{cell} > 0.6 \)), changes in the diurnal LST variation were negligible. Such findings suggest that even the early stages of urbanization can have effects on the diurnal LST variation, and, correspondingly, mitigation of the adverse effects of this process is not effective until the \( UI_{cell} \) value is reduced to approximately 0.6 or lower. A higher summertime diurnal LST variation in an urban environment is generally associated with higher daytime maximum temperatures, which can make outdoor activities less comfortable and pose a greater risk to public health. The \( UI_{cell} \) value of 0.6 warrants further attention because cells dominated by built-up land cover (\( pb > 2/3 \)) have been found to possess \( UI_{cell} \) values of approximately 0.6 or higher in three Asian cities, namely Taipei, Kyoto, and Tokyo (Hung et al., 2010). Fig. 10 indicates that the urbanization indices in the three cities all show a unique pattern in that almost all cells have

\[
UI_{cell} < pb, \text{ when } UI_{cell} \leq 0.6, \text{ and }
\]

\[
UI_{cell} > pb, \text{ when } UI_{cell} > 0.6.
\]

This is because cells dominated by built-up land cover (\( UI_{cell} > 0.6 \)) mostly display negative \( NDVI_{cell} \) values, whereas those with sufficient vegetation cover exhibit positive \( NDVI_{cell} \) values. Addi-

![Fig. 9. Temporal changes of the average urbanization indices of S2 and S4. Average urbanization indices of the S2 were calculated based on values of the middle three cells in the east-west orientation shown in Fig. 5.](image)

Adapted from Hung et al. (2010).
tionally, considering the similar \( U_{cell} \sim p_2 \) patterns found in these three Asian cities, we consider that the same approach can be applied to other cities with comparable landscape patterns and are likely to have similar \( \Delta LST - U_{cell} \) relationships, albeit with various degrees of uncertainty.

Built-up areas such as buildings and paved surfaces have higher thermal inertia compared with vegetation-covered environments (Nasipuria et al., 2006). Hence, with the same amount of heat absorption, the rise in LSTs is lower for built-up surfaces than for vegetation-covered surfaces. A higher degree of urbanization is associated with a higher coverage ratio of built-up surfaces in a cell, resulting in heightened average thermal inertia, which in turn leads to a slower rise in LST per fixed amount of heat absorption. Because the diurnal temperature variation is dependent on the ratio of heat absorption and the thermal inertia of the objects on land surfaces, the fact that higher \( \Delta LST \) values are associated with higher \( U_{cell} \) values implies that urbanization is more likely to result in a higher increase in heat absorption (Qiao et al., 2013; Wouters et al., 2013) than in cell-average thermal inertia. Therefore, measures such as urban parks, community green spaces, green roofs, and cool or permeable pavements (US-EPA, 2014) that can effectively reduce urban heat absorption should be given higher priority in mitigating the UHI effect. However, Georgescu, Morefield, Bierwagen, and Weaver (2014) also reported that the efficacy of these mitigation measures is dependent on geographic and climatic factors. Caution should therefore be exercised when selecting mitigation measures, including careful examination of their geographic and climatic efficacy.

The positive \( \Delta LST - U_{cell} \) correlations determined in this study not only provide a theoretical basis for promoting urban green space but also demonstrate the advantages of using the cell-average urbanization index \( U_{cell} \), which is inherently based on two competing factors, namely the percentage of built-up land cover and the NDVI. The \( U_{cell} \) values can be used to identify locations with higher degrees of urbanization within the study area, and then the \( \Delta LST - U_{cell} \) relationships can facilitate explaining and quantitatively evaluating the impact of urbanization on the diurnal LST variation.

5. Conclusions

We investigated the impact of urbanization on urban landscape patterns and diurnal LST variation in Taipei by using SPOT and MODIS satellite images captured over a period of 17 years. An urbanization index at 1-km spatial resolution was adopted as a quantitative measure of urbanization-induced changes in landscape patterns. Changes in the urbanization indices in different subregions within the study area and the effects of urbanization on the diurnal LST variation were assessed. A few concluding remarks are outlined as follows:

1. Because of the combined effects of several major projects and policies, the degree of urbanization in the study area decreased during 1994–2007, whereas it increased slightly in 2010 because of developments in several subregions.
2. Although the overall urbanization indices decreased during 1994–2007, changes in urbanization indices in certain newly developed subregions were not consistent with the overall pattern. Specifically, developments in these subregions have accelerated in recent years, possibly because of the land-use deregulation plan effective from 2008 onward. The analyses demonstrate that, at least for a midsized city like Taipei, decisions and policies on urban development can have a relatively quick effect on landscape patterns.
3. The diurnal LST variation increases with the urbanization index. In our study area, the diurnal LST variation mostly ranged from 5 to 20°C.
4. The adverse effects of urbanization on the diurnal LST variation are more substantial in the earlier stages of urbanization, and efforts aimed at mitigating the adverse effect are less effective unless the urbanization index is reduced to approximately 0.6 or lower.
5. The urbanization index can quantify the average effect of urbanization on the diurnal LST variation. The relationship between the urbanization index and the diurnal LST variation established by this study can provide estimates of the latter with a standard error of approximately 2.5–3.5°C.
6. Urbanization is likely to result in a greater increase in urban heat absorption than in thermal inertia. Therefore, if they are developed according to geographic and climatic considerations, measures that can reduce urban heat absorption such as urban parks, community green spaces, green roofs and cool (or permeable) pavements should be given higher priority in mitigating UHI effects.

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References


