

Landsat Time-series Images-based Urban Heat Island Analysis: The Effects of Changes in Vegetation and Built-up Land on Land Surface Temperature in Summer in the Hanoi Metropolitan Area, Vietnam

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ABSTRACT

Rapid and unplanned urbanization leads to temperature rise, urban vegetation decrease and built-up land increase, forming an urban heat island (UHI). This study investigated the effects of changes in vegetation and built-up land on land surface temperature (LST) in summer, based on remotely sensed images. LST was first retrieved by means of the Radiative Transfer Model (RTM). Scatter-plots and an univariate linear regression model (ULRM) were first employed to independently measure the influence of NDVI on LST, and of NDBI on LST, respectively. In order to assess the effects of changes in vegetation and built-up land on LST, a multivariate linear regression model (MLRM) was finally employed to improve the accuracy of the predicted model in the identification of the joint effect of both the normalized difference vegetation index (NDVI) and the normalized difference built-up index (NDBI) on LST. The result from the case from the Hanoi Metropolitan Area (HMA), Vietnam using Landsat-5 TM and Landsat-8 OLI/TIRS time-series images during the 1996-2016 period shows that there exists a negative effect of built-up land and a positive effect of vegetation on LST. In addition, indications of intensifying UHI effects were detected in the HMA, especially tending to expand faster and wider to the parts of western, north-western and south-western HMA during the 1996-2007 period. These findings suggest that vegetation weakens the effect of UHIs, whereas, built-up land greatly strengthens the effect of UHIs in the HMA.

1. INTRODUCTION

An UHI is a metropolitan area which is defined by the huge differences between urban and suburban/rural temperatures (Liu and Zhang, 2011). Based on the spatial occurrence, UHIs were classified into two types: surface urban heat islands (SUHIs) and atmospheric urban heat islands (AUHIs) (Ranagalage et al., 2017). Estoque et al. (2017) indicated SUHIs can be detected based on LST, whereas, AUHIs can be identified through air temperature. SUHIs tend to be strongest during the day when the sun is shining (Ranagalage et al., 2017). The buildings, concrete, asphalt, industrial activities and heat from vehicles, factories and air conditioners in urban areas are the main causes of UHIs (Liu and Zhang, 2011). A few studies have discovered the main negative impacts of SUHIs on humans and

environments such as the weakening of living environments and an increased mortality rate (Ranagalage et al., 2017), the adverse health effects (Tan et al., 2010), and the worsen local weather and climate (Liu and Zhang, 2011). Thus, the analysis of UHIs plays an important role in the urban environmental protection and sustainability. UHIs mainly appear around high LST areas which are governed by high surface heat fluxes and obviously affected by urbanization (Dousset and Gourmelon, 2003; Sun et al., 2010; Liu and Zhang, 2011). A higher level of exchange of these surface heat fluxes was found with more vegetated and built-up areas (Oke, 1982). Therefore, in order to understand the formation of UHIs in UHI studies, it becomes vital to explore the effects of both vegetation coverage and built-up land on LST.

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Traditionally, UHI analysis can be carried out based on LSTs measured at meteorological stations (Lu et al., 2009). However, the uneven distribution and limited conditions of these in situ measurements may result in the measured LSTs not fully representing the distribution of LSTs across the big region (Liu and Zhang, 2011). Another limitation of this approach is the near impossibility of capturing enough LSTs over a large area (Vu and Nguyen, 2018b). The occurrences of remote sensing technology overcome those limitations of traditional methods. Compared to LST traditional measurements, remotely sensed images have their advantages of high-resolution, wide-coverage and intensive-points, etc. (Liu and Zhang, 2011), which make UHI studies become easier. UHI studies are mainly based on the spatial distribution of LST. The first studies of UHIs based on satellite-derived LST retrieval were carried out mainly using low-resolution NOAA AVHRR images (Balling and Brazel, 1988; Gallo et al., 1993). Since remotely sensed images of high resolution thermal infrared (TIR) satellite sensors such as 120-m resolution Landsat MSS and TM, 60-m resolution ETM+, and recently 100-m resolution TIRS started to be freely distributed, these data have also been widely utilized to derive LSTs for UHI studies (Liu and Zhang, 2011; Lu et al., 2009; Ranagalage et al., 2017; Ongsomwang et al., 2018; Sanecharoen et al., 2019). With the help of geographic information systems (GIS) techniques, many previous SUHI studies have successfully estimated the effects of urban landscape composition and pattern on LST (Ranagalage et al., 2017; Bokaie et al., 2016; Estoque et al., 2017; Kikon et al., 2016; Liu and Zhang, 2011; Weng et al., 2004). NDVI and NDBI have been considered as the most commonly used landscape indices for examining the spatial and temporal variations of LST (Kumar and Shekhar, 2015; Ranagalage et al., 2017). The first studies on the relationship between LST and vegetation cover using the NDVI were carried out by Goward et al. (2002) and Weng (2001). Later, both these indices were used as land cover types (Zhang et al., 2009). Recent studies have shown that there exists a negative correlation of LST with NDVI and a positive correlation of LST with NDBI (Liu and Zhang, 2011; Ranagalage et al., 2017; Sanecharoen et al., 2019). In spite of these significant contributions, the main limitation of previous work is that the used method, the ULRM, fails to estimate the interrelationship between variables, thus, leading to low accuracy of

the predicted model in the evaluation of the joint effect of both vegetation cover and built-up land on LST. In order to solve this problem, the MLRM is employed to measure the interaction effects of two variables on the dependent variable instead. Therefore, this research examined the joint impact of both vegetation and built-up land on LST by means of the MLRM instead, using Landsat time-series data acquired at three-time points in summer in the period of 1996-2016 of the HMA (Vietnam). Specific objectives of this study are: (1) to derive LST, NDVI and NDBI from Landsat TM and OLI/TIRS data and analyze their spatio-temporal variations; (2) to apply the MLRM to investigate the joint-effects of both NDVI (vegetation) and NDBI (built-up land) on LST.

2. METHODOLOGY

2.1 Description of the study area

The research was conducted in the HMA, Vietnam, which is located at 20°54'34.14"-21°6'22.69" south latitude and 105°42'16.97"-105°56'21.48" east longitude (Figure 1) with an area of 273.9 km². Vietnam has been experiencing dramatic economic growth since the Doi Moi Policy started in 1986 (Logan, 2005) which has greatly contributed to the rapid urbanization in Hanoi city (Tsunoda et al., 2014), particularly after Hatay province, Vinhphuc province's Melinh district and the four communes of Luongson district, Hoabinh province were merged into the metropolitan area of Hanoi from August 2008 (Hiep, 2014). Therefore, rapid urban development displaced vegetation in many areas, especially in the HMA. Hanoi is now the largest city in Vietnam with an estimated population of 8.05 million and a population density of 2,300 people for every square kilometer in 2019. It has a tropical monsoon climate with wet and dry seasons. The dry and wet seasons extend from November to April and from May to September, respectively (Garcia et al., 2006).

2.2 Data used

The remote sensing data used in the change detection should be obtained from a sensor system that acquires data at approximately the same time of day (Star et al., 1997) or at near anniversary dates to minimize inconsistencies in sun angle or phenology (Jensen, 2009). However, it is not possible to obtain extract (or near) anniversary dates in the HMA because of Landsat orbit changes and monthly average cloud cover of 72.4% (Lasko et al., 2018).

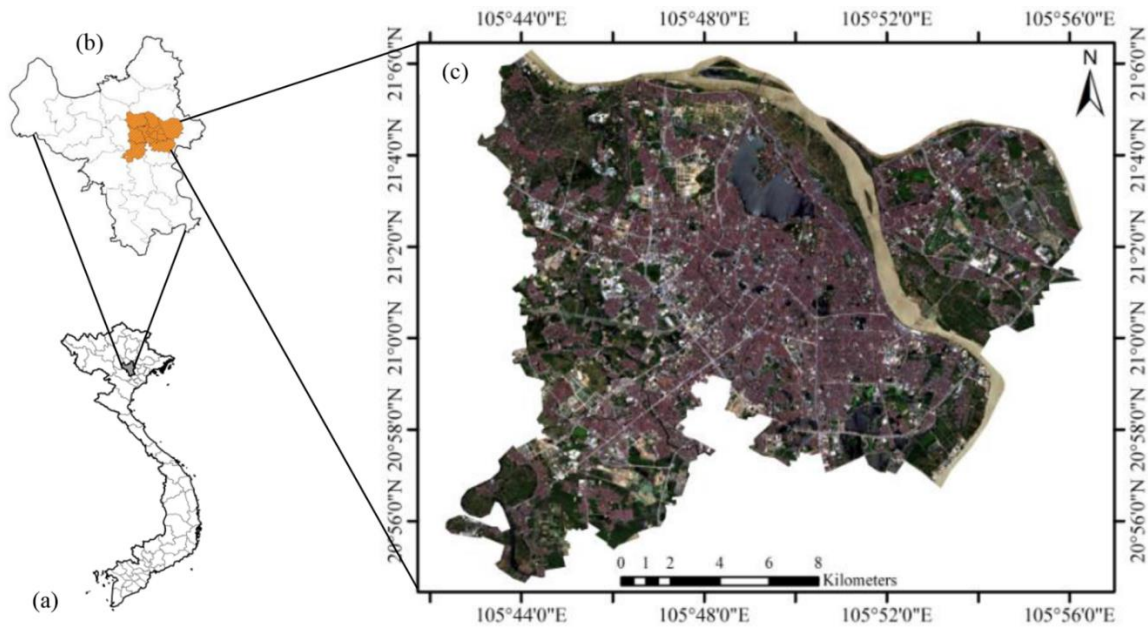


Figure 1. The study area: (a) Vietnam, (b) Hanoi city, and (c) the Hanoi metropolitan area (2016 Landsat-8 OLI true color composite)

Therefore, daytime Landsat images (path 127, row 045/046) with 30-m spatial resolution freely distributed by the U.S. Geological Survey acquired in the wet (summer) season of 1996, 2007 and 2016 were collected (Table 1) in this study. All the Landsat images projected in the UTM Zone N48 and WGS 1984 ellipsoid datum were the Precision and Terrain Correction products (Vu and Nguyen, 2018b). The multispectral bands of the Landsat-5 TM and Landsat-8 OLI data have 30-m spatial resolution, while the thermal band 6 of Landsat-5 TM and

thermal bands 10 and 11 of Landsat-8 TIRS have 120-m and 100-m spatial resolution, respectively and were resampled to 30 meter pixels. In addition, reference data of a total of 400 sample points randomly selected from high resolution images in Google Earth Maps and the field survey data of nine air temperatures measured by meteorological stations (Table 2) were also collected for the accuracy assessment of built-up land and LST derived from Landsat images, respectively.

Table 1. Descriptions of Landsat-5 TM and Landsat-8 OLI/TIRS datasets

Sensor	Date of acquisition (Y-M-D)	Time of acquisition (hh:mm:ss)	Path/Row	Spatial resolution of bands (m)	Cloud cover (%)	Image quality
TM	1996-9-30	02:41:56.28	127/045	30	2.00	9/9
TM	1996-9-30	02:42:20.18	127/046	30	10.00	9/9
TM	2007-5-24	03:17:49.46	127/045	30	1.00	7/9
TM	2007-5-24	03:18:13.30	127/046	30	19.00	7/9
OLI, TIRS	2016-6-01	03:23:04.77	127/045	30	13.03	9/9
OLI, TIRS	2016-6-01	03:23:28.67	127/046	30	13.74	9/9

2.3 Identification of the relationship between LST, vegetation and built-up land

2.3.1 Image pre-processing

The image pre-processing process involves two steps. The first step involves the conversion of the DN data (Q_{cal}) to top of atmosphere (ToA) radiance ($L_{ToA,\lambda}$) using inflight sensor calibration parameters in

the metadata file. The conversion of (Q_{cal})-to- ($L_{ToA,\lambda}$) for Landsat-5 TM data (Chander et al., 2009; Vu and Nguyen, 2018a) and Landsat-8 OLI/TIRS data (Nguyen and Vu, 2019; Zanter, 2016) are performed using Equation (1) and (2), respectively:

$$L_{ToA,\lambda} = \left(\frac{L_{max,\lambda} - L_{min,\lambda}}{Q_{cal,max} - Q_{cal,min}} \right) \times (Q_{cal} - Q_{cal,min}) + L_{min,\lambda} \quad (1)$$

Where; $L_{TOA,\lambda}$ is ToA spectral radiance [$W/m^2 \cdot sr \cdot \mu m$] at the wavelength λ (μm); Q_{cal} is DN values; Q_{cal_min} and Q_{cal_max} are minimum and maximum DN values corresponding to $L_{min,\lambda}$ and $L_{max,\lambda}$, respectively; $L_{min,\lambda}$ and $L_{max,\lambda}$ are ToA spectral radiance [$W/m^2 \cdot sr \cdot \mu m$].

$$L_{TOA,\lambda} = M_L Q_{cal} + \Delta_L \quad (2)$$

Where; $L_{TOA,\lambda}$ is ToA spectral radiance [$W/(m^2 \cdot sr \cdot \mu m)$] at the wavelength λ (μm); M_L and Δ_L are the radiance multiplicative scaling factor and the radiance additive scaling factor for the bands, respectively; Q_{cal} is the DN value.

After the Q_{cal} -to- $L_{TOA,\lambda}$ conversion, the second step involves compensating for atmospheric effects for Landsat reflective bands using the FLAASH algorithm (Adler-Golden et al., 1999). The spectral radiance is determined using Equation (3) (Adler-Golden et al., 1998; Adler-Golden et al., 1999):

$$L^* = \left(\frac{A\rho}{1-\rho_e S} \right) + \left(\frac{B\rho_e}{1-\rho_e S} \right) + L_a^* \quad (3)$$

Where; ρ is the pixel surface reflectance; ρ_e is an average surface reflectance for the pixel and a surrounding region; S is the spherical albedo of the atmosphere; L_a^* is the radiance backscattered by the atmosphere; A and B are coefficients that depend on atmospheric and geometric conditions but not on the surface. The values of A , B , S and L_a^* are determined based on MODTRAN4 (Ahmadian et al., 2016). After the water retrieval, the spatially averaged reflectance ρ_e is estimated using Equation (4) (Adler-Golden et al., 1998; Adler-Golden et al., 1999):

$$L_e = \left(\frac{(A+B)\rho_e}{1-\rho_e S} \right) + L_a^* \quad (4)$$

2.3.2 Land surface temperature retrieval

Using the RTM-based method, LST can be retrieved from Landsat-5 using band 6 and Landsat-8 TIRS using band 10 with an accuracy of lower than 0.6 K and 1 K, respectively (Vu and Nguyen, 2018b). Therefore, in this study, this method was applied to obtain LST from Landsat-5/ Landsat-8 TIR data acquired in 2007 and 2016, respectively. LST in the TIR region can be retrieved using Equation (5) (Barsi et al., 2003; Vu and Nguyen, 2018b):

$$L_{TOA,\lambda} = \tau_\lambda [\varepsilon_\lambda B_{b,\lambda}(T_s) + (1 - \varepsilon_\lambda) L_{atm,\lambda}^\downarrow] + L_{atm,\lambda}^\uparrow \quad (5)$$

Where; $L_{TOA,\lambda}$ is the TOA radiance [$W/(m^2 \cdot sr \cdot \mu m)$] determined from Equation (1) and (2); ε_λ is the land surface emissivity (LSE); $B_{b,\lambda}(T_s)$ is the blackbody radiance [$W/(m^2 \cdot sr \cdot \mu m)$] given by the Planck's law and T_s is the LST (Kelvin); $L_{atm,\lambda}^\uparrow$ is the upwelling atmospheric radiance [$W/(m^2 \cdot sr \cdot \mu m)$]; $L_{atm,\lambda}^\downarrow$ is the downwelling atmospheric radiance [$W/(m^2 \cdot sr \cdot \mu m)$] and τ_λ is the total atmospheric transmissivity between the surface and the sensor (Vu and Nguyen, 2018b).

In this study, the result of Sobrino et al. (2008) was used to estimate the LSE by means of the NDVI-based threshold approach. The LSE is calculated in three cases: (i) if $NDVI < NDVI_{soil}$ then the pixel is considered mainly covered by bare soil, and a mean value of 0.97 is assumed for the LSE of soil (ε_s) (Vu and Nguyen, 2018b); (ii) $NDVI < NDVI_{veg}$ if then the pixel corresponds to dense vegetation areas (fully vegetated), and the LSE of vegetation (ε_v) is given a value of 0.99 (Sobrino et al., 2008; Vu and Nguyen, 2018b); (iii) if $NDVI_{soil} < NDVI < NDVI_{veg}$ then each pixel is considered a mixing of bare soil and vegetation, and the LSE is estimated using (6):

$$\varepsilon_i = f_v \cdot \varepsilon_v + (1 - f_v) \cdot \varepsilon_s \quad (6)$$

Where; ε_i is the LSE of pixel i ; ε_v and ε_s are the LSE of vegetation and soil; and f_v is the vegetation fraction retrieved from Equation (7). LST was finally retrieved using Equation (8):

$$f_v = \left(\frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \right)^2 \quad (7)$$

Where; $NDVI_{soil}$ and $NDVI_{veg}$ are the NDVI values corresponding to bare soil and full vegetation cover, respectively.

$$T_s = \frac{K_2}{\ln \left[\frac{K_1}{B_{b,\lambda}(T_s)} + 1 \right]} - 273.16 \quad (8)$$

Where; K_1 and K_2 are calibration constant 1 [$W/(m^2 \cdot sr \cdot \mu m)$] and calibration constant 2 (Kelvin), respectively; $B_{b,\lambda}(T_s)$ is the blackbody radiance [$W/(m^2 \cdot sr \cdot \mu m)$]; and $\ln$ is the natural logarithm.

2.3.3 Vegetation coverage and built-up land estimation

The NDVI can be considered as indications of the presence of vegetation and amount or condition

of vegetation on pixel basis (Orhan et al., 2014; Ranagalage et al., 2017), whereas, the NDBI is an index for extracting built-up areas (Zha et al., 2003). The positive NDBI values indicate built-up areas and those close to 0 indicate vegetation, while the negative values represent water bodies (Ranagalage et al., 2017). NDVI and NDBI are expressed as Equation (9) and (10), respectively:

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \quad (9)$$

$$NDBI = \frac{R_{MIR} - R_{NIR}}{R_{MIR} + R_{NIR}} \quad (10)$$

Where; R_{RED} , R_{NIR} , and R_{MIR} are the surface reflectance of the red band (band 3 in Landsat-5 TM and band 4 in Landsat-8 OLI), of the near-infrared band (band 4 in Landsat-5 TM and band 5 in Landsat-8 OLI), and of the short wavelength infrared band (band 5 in Landsat-5 TM and band 6 in Landsat-8 OLI), respectively.

2.3.4 Identification of the relationship between LSTs, vegetation and built-up land

After the values of LST, NDVI, and NDBI extracted from multi-spectral Landsat-5 TM and Landsat-8 OLI/TIRS images, a total of 304,306 points converted from raster data were used for the identification of the effects of changes in vegetation and built-up land on LST in the HMA. In this process, in order to investigate these effects, scatter-plots and the ULRM were first employed to independently measure the influence of NDVI on LST, and of NDBI on LST. As discussed above, the ULRM fails at estimating the interrelationship between variables, thus, leading to low accuracy of the predicted model in the evaluation of the joint

effect of both vegetation and built-up land on LST. Therefore, the MLRM was finally applied to improve the accuracy of the predicted model in the identification the joint effect of both NDVI and NDBI on LST.

3. RESULTS AND DISCUSSION

3.1 LST in 1996, 2007 and 2016

Data from Table 2 illustrates the minimum and maximum differences in values between estimated LSTs and the meteorological air temperatures (MATs) were 1.1-4.2 °C, 0.9-4.0 °C and 0.6-4.0 °C at the three time points, respectively. These positive differences are similar to those reported in previous studies of Chan et al. (2018) and Rhee and Im (2014) that the day LST is higher than air temperature. The two main metrics, root mean square error (RMSE) and mean absolute error (MAE), were determined with the values of 2.3 °C and 2.0 °C on 30 September 1996, 2.6 °C and 2.6 °C on 24 May 2007, and 2.2 °C and 1.9 °C on 01 June 2016. In addition, regression analysis between Landsat-retrieved LSTs and the MATs is shown in scatter-plots in Figure 2. Examinations of the results show that there existed significant high correlation coefficients of 0.911, 0.897 and 0.845 between LSTs and MATs corresponding with relatively high R-squared values of 0.831 in 1996, 0.714 in 2007 and 0.804 in 2016 (statistically significant at the 0.05 level). RMSE and MAE values ranged between 2.2 °C and 2.6 °C, and 1.9 °C and 2.6 °C and high correlation coefficients and R-square values for regression models indicate that these LSTs retrieved from Landsat-5/ Landsat-8 TIR images can be used for the investigation the effects of changes in vegetation and built-up land on LST in this study.

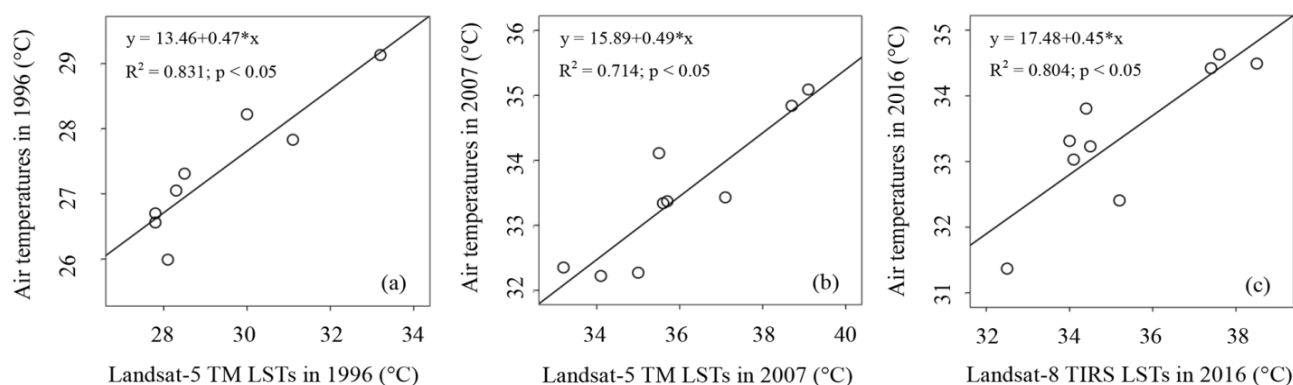
Table 2. Summary of validation results for LSTs obtained from Landsat-5/ Landsat-8 TIR data.

Station names	H (m)	Temperatures (°C)														
		1996-9-30					2007-5-24					2016-6-01				
		T ₂	T ₃	T ₂₋₄₂	T _{L5}	Dif.	T ₃	T ₄	T ₃₋₁₈	T _{L5}	Dif.	T ₃	T ₄	T ₃₋₂₃	T _{L8}	Dif.
Bacgiang	7.501	26.5	28.4	27.8	31.1	3.3	33.1	34.2	33.4	37.1	3.7	33.5	34.3	33.8	34.4	0.6
Sondong	58.473	27.8	29.7	29.1	33.3	4.2	34.7	36.0	35.1	39.1	4.0	34.3	34.8	34.5	38.5	4.0
Lucngan	14.646	25.7	28.0	27.3	28.5	1.2	34.6	35.4	34.8	38.7	3.9	34.4	35.0	34.6	37.6	3.0
Hiephoa	20.565	27.1	28.7	28.2	30.0	1.8	32.8	34.6	33.3	35.6	2.3	34.0	35.1	34.4	37.4	3.0
Langson	257.881	25.3	27.1	26.6	27.8	1.2	32.0	32.9	32.3	35.0	2.7	32.1	32.9	32.4	35.2	2.8
Huulung	41.479	-	-	-	-	-	33.6	35.3	34.1	35.5	1.4	32.8	33.4	33.0	34.1	1.1
Thatkhe	162.452	24.1	26.8	26.0	28.1	2.1	31.8	33.2	32.2	34.1	1.9	32.7	34.3	33.3	34.0	0.7

Table 2. Summary of validation results for LSTs obtained from Landsat-5/ Landsat-8 TIR data (cont.).

Station names	H (m)	Temperatures (°C)														
		1996-9-30					2007-5-24					2016-6-01				
		T ₂	T ₃	T ₂₋₄₂	T _{L5}	Dif.	T ₃	T ₄	T ₃₋₁₈	T _{L5}	Dif.	T ₃	T ₄	T ₃₋₂₃	T _{L8}	Dif.
Bacson	395.081	25.3	27.3	26.7	27.8	1.1	31.9	33.4	32.4	33.2	0.9	31.1	31.8	31.4	32.5	1.1
Dinhlap	190.645	25.3	27.8	27.1	28.3	1.3	33.1	34.0	33.4	35.7	2.3	33.0	33.6	33.2	34.5	1.3
Accuracies		RMSE =					RMSE =					RMSE =				
		MAE =					MAE =					MAE =				
		2.3					2.6					2.2				
		2.0					2.6					1.9				

Notes: H are heights above mean sea level of meteorological stations in meters; T₂, T₃ and T₄ are the air temperatures measured by six meteorological stations at 1.5 m above ground at 2 AM, 3 AM and 4 AM (GMT) corresponding to local times of 9 AM, 10 AM and 11 AM in Vietnam; T₂₋₄₂, T₃₋₁₈ and T₃₋₂₃ are the interpolated air temperatures on 30th September 1996 at 2:42 AM, on 24th May 2007 at 3:18 AM and on 01 June 2016 at 3:23 AM from meteorological data monitored at from 2 AM to 3 AM and at from 3 AM to 4 AM; T_{L5}, T_{L8} and Dif. are LSTs retrieved from Landsat-5/ Landsat-8 TIR data and the value differences between LSTs and interpolated MATs, respectively; - represents no available data.

**Figure 2.** Scatter-plots of between meteorological air temperatures and LSTs obtained from Landsat-5/ Landsat-8 TIR images

The distribution of LSTs retrieved from TIR bands of 1996 and 2007 Landsat-5, and 2016 Landsat-8 images in the HMA is shown in Figures 3 and 4. The descriptive statistics of LSTs are summarized in Table 3. The LST in HMA ranged from 20.02 °C to 38.01 °C with a mean of 26.45 °C on 30 September 1996 (02:41:56.28 GMT). LST varied in the range of from 18.72 °C to 54.83 °C with a mean of 38.81 °C on 24 May 2007 (03:17:49.46 GMT), whereas, on 01 June 2016 (03:23:04.77 GMT), LST ranged from 26.83 °C to 66.93 °C with a mean value of 42.93 °C. In general, higher LSTs were detected mostly in the core urban areas of the HMA. Small areas of high LSTs were mostly found in the center in 1996 (Figure 3(a)). By 2007 and 2016, however, high LST areas had greatly expanded towards the western, north-western and south-western parts of the HMA. A recent study carried out by Nguyen et al. (2019) also indicated that, by 2009 and 2016, Hanoi's residential areas developed and expanded to these directions of the city. Meanwhile, the area of high LSTs was almost unchanged in the period of 2007-2016 (Figure 3(b))

and (c)). Data from histograms and boxplots in Figure 4 demonstrates that the distribution of the LST was strongly right-skewed in 1996 dominated by many very high LSTs, left-skewed in 2007 and fairly balanced in 2016. LSTs were mainly concentrated in the range of 24 °C-30 °C in 1996, 30 °C-47 °C in 2007 and 36 °C-55 °C in 2016. It can be clearly seen that the high LST areas had been increasing rapidly during 1996-2016 and tends to expand towards the western, north-western and south-western parts. The increase of buildings, concrete, asphalt in residential areas in the city centre and the northwest, and newly built areas of residential housing and industrial activities in the west and southwest during 1999-2016 (Nguyen et al., 2019) may have accounted for the increasing of LSTs in these directions. In addition, the rapid increase of vehicles such as motorcycles and cars (Tuan and Shimizu, 2005) and of air conditioners from zero to 0.13 million units during 1985-2005 (Nguyen et al., 2009) also greatly contributed heat transferred to the land surface of the Earth.

Table 3. Descriptive statistics of the LST, NDVI and NDBI in the HMA.

Date	Time (GMT)	Minimum	Median	Mean	Maximum
1996-9-30	02:41:56.28	20.02	26.01	26.45	38.01
2007-5-24	03:23:04.77	18.72	39.17	38.81	54.83
2016-6-01	03:17:49.46	26.83	42.83	42.93	66.93

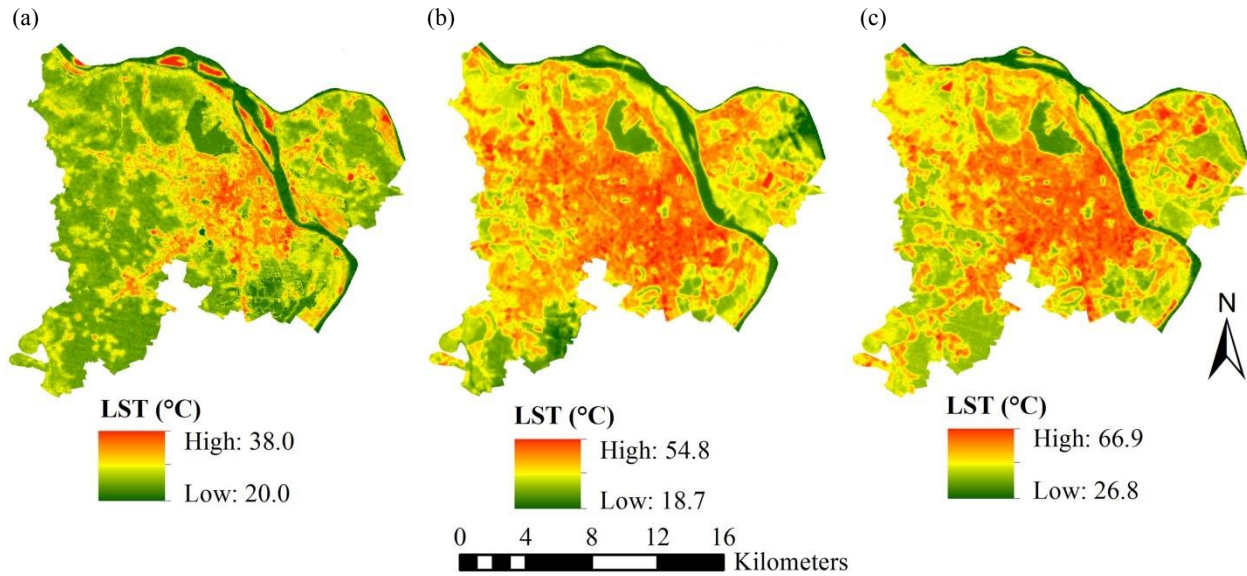


Figure 3. Land surface temperatures in 1996, 2007 and 2016

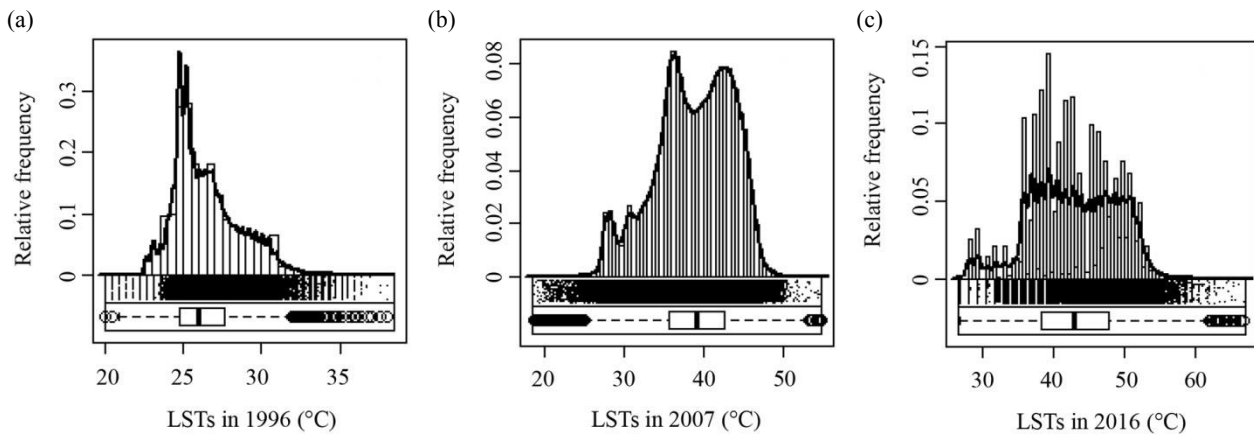


Figure 4. Histograms, density traces, 1-D scatter-plot and box-plots of LSTs retrieved in 1996, 2007 and 2016

3.2 NDVI in 1996, 2007 and 2016

The distribution of NDVI in the HMA in 1996, 2007 and 2016 are shown in Figures 5 and 6, and their statistics are summarized in Table 4. Data from Table 4 demonstrates NDVI values ranged from -1 to 1 at the three-time points. The mean values of 0.46 in 1996, 0.37 in 2007 and 0.4 in 2016, and median NDVI values of 0.5 in 1996, 0.36 in 2007 and 0.4 in 2016 proves vegetation cover decreased gradually during this period, especially from 1996 to 2007. Data from Figure 5 shows that areas of high NDVI values were mainly detected in the western, north-western and

south-western parts of the HMA at these three-time points, whereas, areas of low NDVI were mainly concentrated in the core urban areas of the HMA. Data from histograms and boxplots in Figure 6 demonstrates that the distribution of the NDVI was strongly left-skewed with many low NDVI values dominating the plot. The order of the left-skewness is of NDVI in 2016, 2007 and 1996, respectively corresponding to the decrease of NDVI over the three-time points. Forests in the west and active agricultural land in the southwest and northwest of the HMA (Nguyen et al., 2019) have accounted for the

higher NDVI values, whereas, the crowded residential areas in the city centre and industrial zone in suburban areas causing low density of vegetation

cover (Hoang, 2016; Hoang, 2017) were the causes of low NDVI values.

Table 4. Descriptive statistics of the NDVI in the HMA

Date	Time (GMT)	Minimum	Median	Mean	Maximum
1996-9-30	02:41:56.28	-1.00	0.50	0.46	1.00
2007-5-24	03:23:04.77	-1.00	0.36	0.37	1.00
2016-6-01	03:17:49.46	-1.00	0.40	0.40	1.00

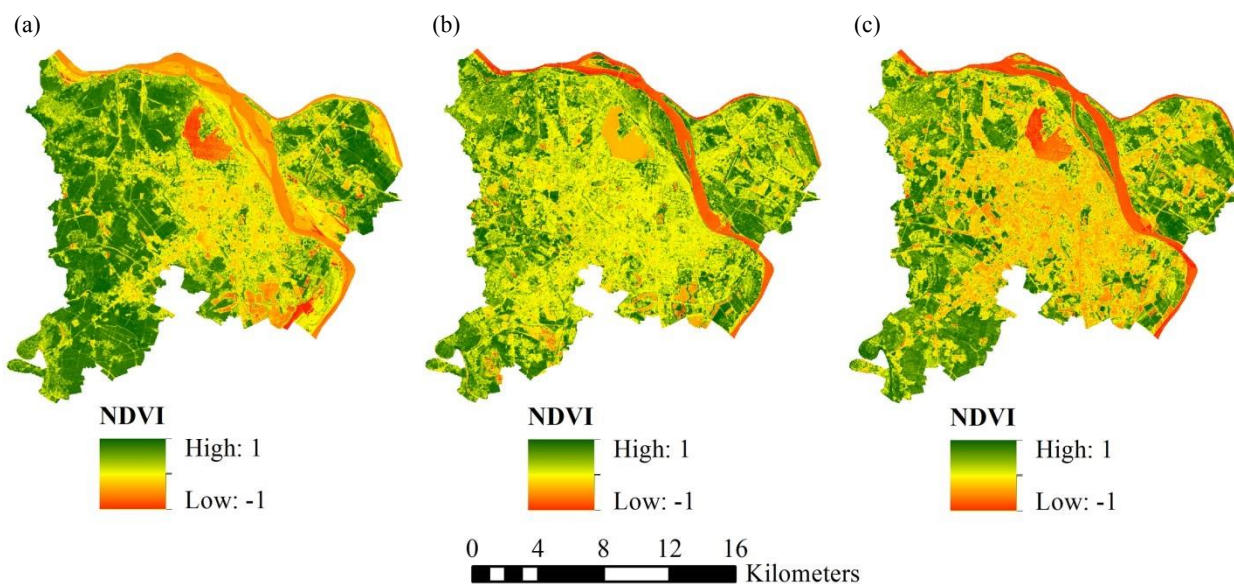


Figure 5. NDVI in 1996, 2007 and 2016

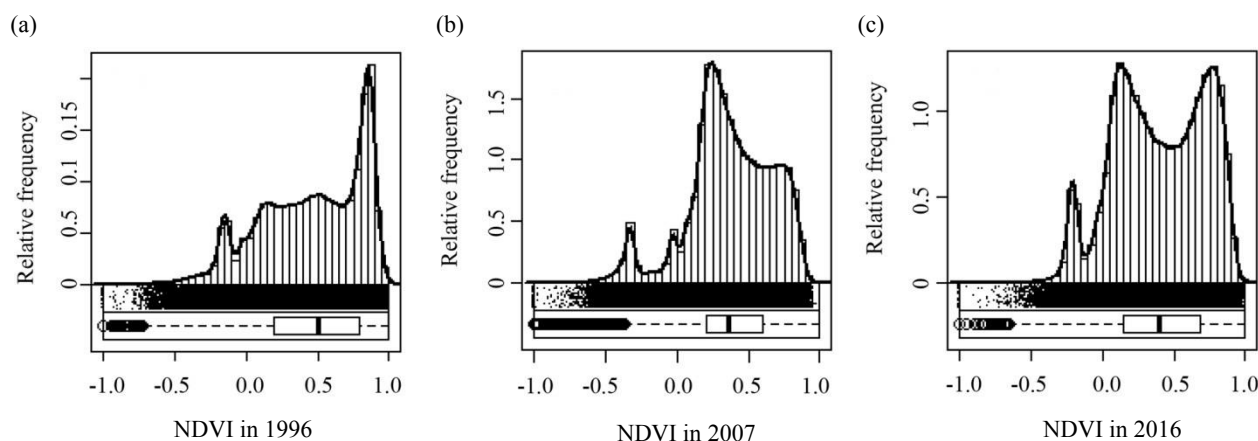


Figure 6. Histograms, density traces, 1-D scatter-plot and box-plots of the NDVI in 1996, 2007 and 2016

3.3 NDBI in 1996, 2007 and 2016

Data from Table 5 demonstrates that the extracted built-up land using NDBI from 2016 Landsat-8 images resulted in a overall accuracy of 89.3% with a kappa statistic of 0.79. The confusion matrix along with user's and producer's accuracies of more than 80% for built-up land map are also provided in Table 5. These accuracies meet the 80%

accuracy standard of the United States National Vegetation Classification (Grossman et al., 1998). This result indicates that the combination of Landsat images and NDBI can be used reliably for the built-up land extraction and for the investigation of the effects of changes in vegetation and built-up land on land surface temperature in this study.

Table 5. Summary of accuracy assessment of the extracted built-up land.

Land cover types	Built-up land	Others	Classification overall	Producer's Accuracy	User's Accuracy	Overall accuracy	Kappa
Built-up land	181	24	205	90.5	88.3	89.3	0.79
Others	19	176	195	88.0	90.3		
Truth overall	200	200					

The distribution of NDBI values of the HMA obtained from Landsat images acquired in 1997, 2007 and 2017 are shown in Figure 7 and 8, and are statistically summarized in Table 6. Data from this table shows that the values of NDBI ranged from 0.77 to 0.56 in 1996, from -0.45 to 0.48 in 2007 and from -0.64 to 0.58 in 2016. Small areas of high NDBI values were detected in the core urban areas of the HMA in 1997 (Figure 7 (a)). But by 2007 and 2016, high NDBI areas had greatly expanded outside the HMA center, which expands towards the western, north-western and south-western parts of the core urban HMA, especially in the period of 1996-2007 (Figure 7 (b) and (c)). The rapid expansion of high NDBI areas during the period of 1996-2007 was due to the high rate of urbanization after the Doi Moi Policy started in 1986 (Logan, 2005). Data from histograms and boxplots in Figure 8 demonstrates that

the distribution of the NDBI was similar to those of the LST shown in Figure 3. The NDBI was strongly right-skewed in 1996, quite balanced in 2007 and left-skewed in 2016. Similar to those reported by Nguyen et al. (2019), the NDBI had been increasing during this period, especially in the period of 1996-2007. The number of construction and rehabilitation of the city's infrastructure led to the rapid increase of 4870.5 thousand m² of new buildings in Hanoi during 1990-2013 reported by Nguyen et al. (2019) was the most important cause of the increasing of high NDBI areas. In addition, a drastic increase in population from 2685 thousand people in 1999 to 7328.4 thousand people in 2016 (Nguyen et al., 2019), and transformation from natural forests into urban built-up areas (Thanh Hoan et al., 2018) and an increase rate of electricity per capita (Nguyen et al., 2019) have also significantly contributed to those changes of NDBI areas.

Table 6. Descriptive statistics of the NDBI in the HMA.

Date	Time (GMT)	Minimum	Median	Mean	Maximum
1996-9-30	02:41:56.28	-0.77	-0.08	-0.07	0.56
2007-5-24	03:23:04.77	-0.45	-0.07	-0.07	0.48
2016-6-01	03:17:49.46	-0.64	0.02	0.02	0.58

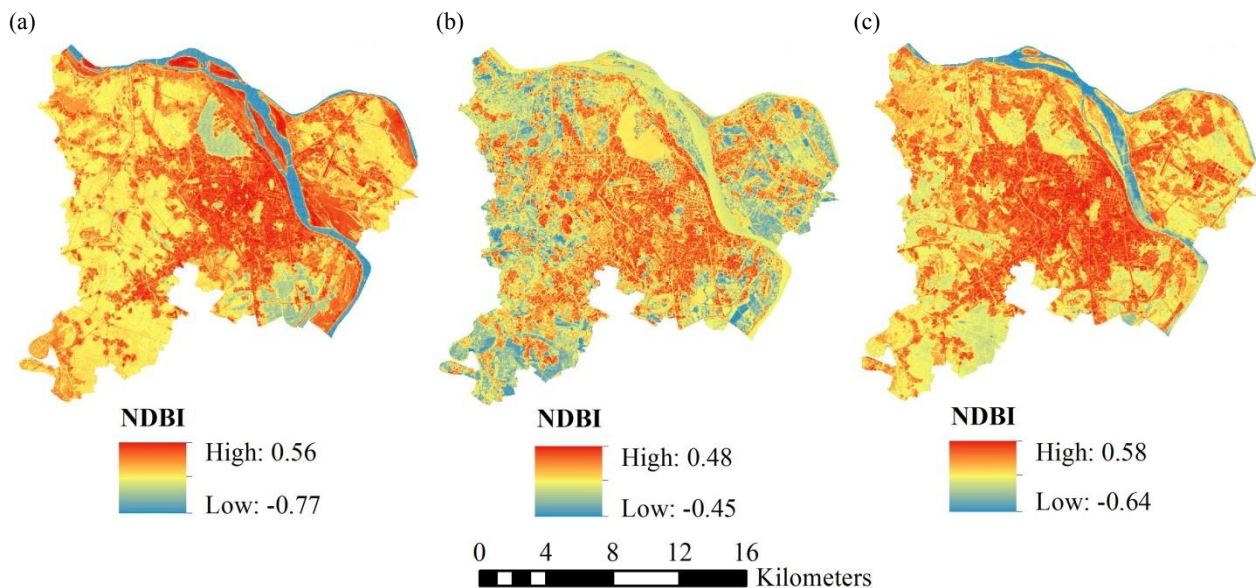


Figure 7. NDBI in 1996, 2007 and 2016

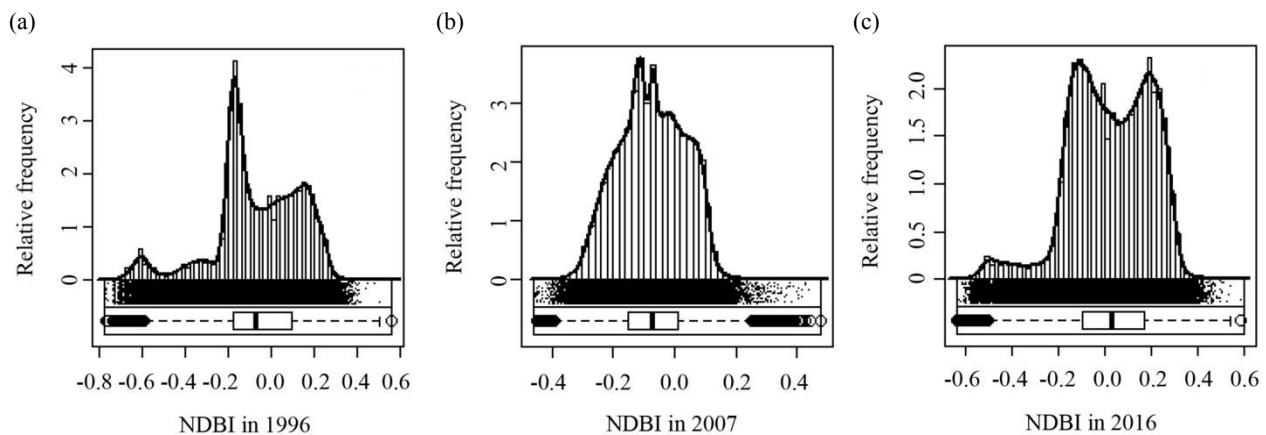


Figure 8. Histograms, density traces, 1-D scatter-plot and box-plots of the NDBI retrieved in 1996, 2007 and 2016

3.4 Spatio-temporal variation of relationship between LSTs, vegetation and built-up land

Data from scatter-plots in Figure 8 show that there were significant negative regression coefficients indicating negative correlations between LST and NDBI ($p < 0.001$) with the values of -1.61 in 1996 and -3.98 in 2016 (Figure 9 (a) and (c)). This indicates LSTs were negatively correlated with vegetation cover. However, opposite to those reported in previous studies (Liu and Zhang, 2011; Ranagalage et al., 2017; Sanecharoen et al., 2019), a significant positive regression coefficient of 0.56 was estimated in 2007 (Figure 9 (b)). In addition, low values of coefficient of determination (R^2) of 0.076 in 1996, 0.001 in 2007 and 0.044 in 2016 indicate a relative bad goodness of fit for the observations. This is due to the existence of a large area of surface water (rivers and lakes) in the study area, which negatively affects the predictive accuracy of the ULRM. Therefore, surface water pixels were removed to re-estimate of the relationship between LST and NDVI. Data from Figure 9 (d), (e) and (f) shows that after the NDVI values of surface water were removed, all of coefficient of determinations had much improved with R^2 of 0.682 in 1996, 0.316 in 2007 and 0.524 in 2016. Although the R^2 values for the last two-time points were not as high as those of 1996, particularly in the year of 2016, they were all statistically significant at the 0.001 level. These regression coefficients were negative and statistically highly significant ($p < 0.001$) at the three-time points showing the LST is strongly and negatively correlated with vegetation cover. Our finding is consistent with those reported in previous studies

(Kumar and Shekhar, 2015; Nguyen et al., 2019; Sanecharoen et al., 2019).

It can be seen in Figure 9 that the NDBI spatial pattern of values shown in Figure 7 considerably mirrors those of LST as shown in Figure 3. This indicates a positive correlation between LST and NDBI. The significant positive regression coefficient between LST and NDBI was low in 1996 due to less urbanization in the HMA at the first time point. Nevertheless, like the correlation between LST and NDVI (vegetation), the correlation between LST and NDBI (built-up land) was also statistically significant at the 0.001 level ($p < 0.001$) with high R^2 values of 0.676 in 1996 and 0.768 in 2016. Although the R^2 value of 0.163 in 2016 was not as high as those of 1996 and 2007, it was still statistically significant ($p < 0.001$). The regression coefficient increases considerably as the area became more urbanized (Ranagalage et al., 2017). Therefore, the increasing of regression coefficients from 8.47 in 1996 to 18.29 in 2007, and to 30.2 in 2016 proves a rapid urbanization process in the HMA during 1996-2016. A significant increase in the area of building land occurred with the increases of 13.18% in the residential area and 2.66% in the industrial area indicated by Nguyen et al. (2019) can be account for this urbanization process. It can be concluded that there existed a very strong positive correlation and relationship between LST and built-up land during the period of 1996-2016. This finding is consistent with those reported in previous studies (Sanecharoen et al., 2019; Zhang et al., 2009), especially in the HMA (Nguyen et al., 2019).

The evaluation of the joint effect of both vegetation cover and built-up land on LST was

carried out using the MLRM. Data from Table 7 shows that, in general, there existed a significant negative relationship (correlation) between LST and NDVI and a significant positive relationship between LST and NDBI at all three-time points, particularly in the case of surface water removed from predicting models. The high R^2 values of 0.742 in 1996 and 0.774 in 2016 proves that 74.2% and 77.4% of the LST were predicted by the NDVI and the NDBI. Although R^2 value of 0.394 in 2007 was not as high as those of the two previous time points, it was statistically significant at the 0.001 level. Generally, the absolute values of regression coefficients of NDBI were greater than those of NDVI indicating the relationship between the LST and the NDBI (Figure 9 (g), (h) and (i)) was stronger than that of between the LST and the NDVI (Figure 9 (d), (e) and (f)). This indicates that the explanatory power of built-up land with regards to the distribution of LST spatial pattern of in the HMA is much stronger than that of vegetation coverage.

Recent studies have shown that vegetation cover has dramatically decreased in urban districts and some areas of suburban districts because of the incessant urbanization process in the central urban areas and some sub-urban areas of the Hanoi city (Hoang, 2016; Hoang, 2017). Particularly, the Doi Moi Policy since 1986 has greatly contributed to the rapid urbanization process in Hanoi city (Tsunoda et al., 2014). Nguyen et al. (2019) also reported that the construction and rehabilitation of the city's infrastructure and the number of industrial establishments has increased by 4,870,500 m², equivalent to an increase rate of 211,760 m²/year since 1990. In addition, high population density

ranged from 21,000 people/km² to 40,000 people/km² in urban districts in 2016 and tends to increase in urban districts since 1990. Similar to those reported in previous studies (Hoang, 2016; Hoang, 2017; Nguyen et al., 2019), the rapid development in these urban areas has brought the replacement of land cover types, especially vegetation cover, with urban built-up land. It is apparent that transitions of land cover types, especially from vegetation and other types to built-up land were the main causes of the increase of LST in the HMA. In addition, the emergence of Hatay province, Vinhphuc province's Melinh district and four communes of Hoabinh province's Luongson district into the metropolitan area of Hanoi in August 2008 (Hiep, 2014) has led a two-fold jump in population with an increase of 3,153,300 people as compared with that of 2007 (Nguyen et al., 2019). A recent study by Nguyen et al. (2019) has also shown that Hanoi had experienced a remarkable change in the total population and population density during 1998-2016. The total population significantly increased from 2,685,000 people in 1999 to 7,328,400 people in 2016 with a rate of increase of 273,140 people per year (Nguyen et al., 2019). It is clear that the change in the total population and population density also accounted for the increase of LSTs. It can be concluded from the above discussion that the increase of built-up land and the decrease in vegetation cover are linked with the increase of LSTs. In addition, the relationship between LSTs and vegetation and built-up land was strongly correlated with continuous increases in population and socio-economic factors in the HMA.

Table 7. MRLMs for predicting LST of HMA

Date	Model	Coefficient of determination (R^2)	Significance level (p)
1996-9-30	LST = -1.498*NDVI + 8.410*NDBI + 27.710	0.742	0.001
	LST* = -3.219*NDVI + 6.060*NDBI + 27.710	0.774	0.001
2007-5-24	LST = 1.784*NDVI + 19.129*NDBI + 39.553	0.174	0.001
	LST* = -8.739*NDVI + 11.306*NDBI + 44.240	0.394	0.001
2016-6-01	LST = 0.944*NDVI + 30.699*NDBI + 41.90	0.770	0.001
	LST* = -0.116*NDVI + 29.906*NDBI + 42.514	0.729	0.001

Notes: *indicates multivariable linear regression models were predicted after surface water pixels were removed.

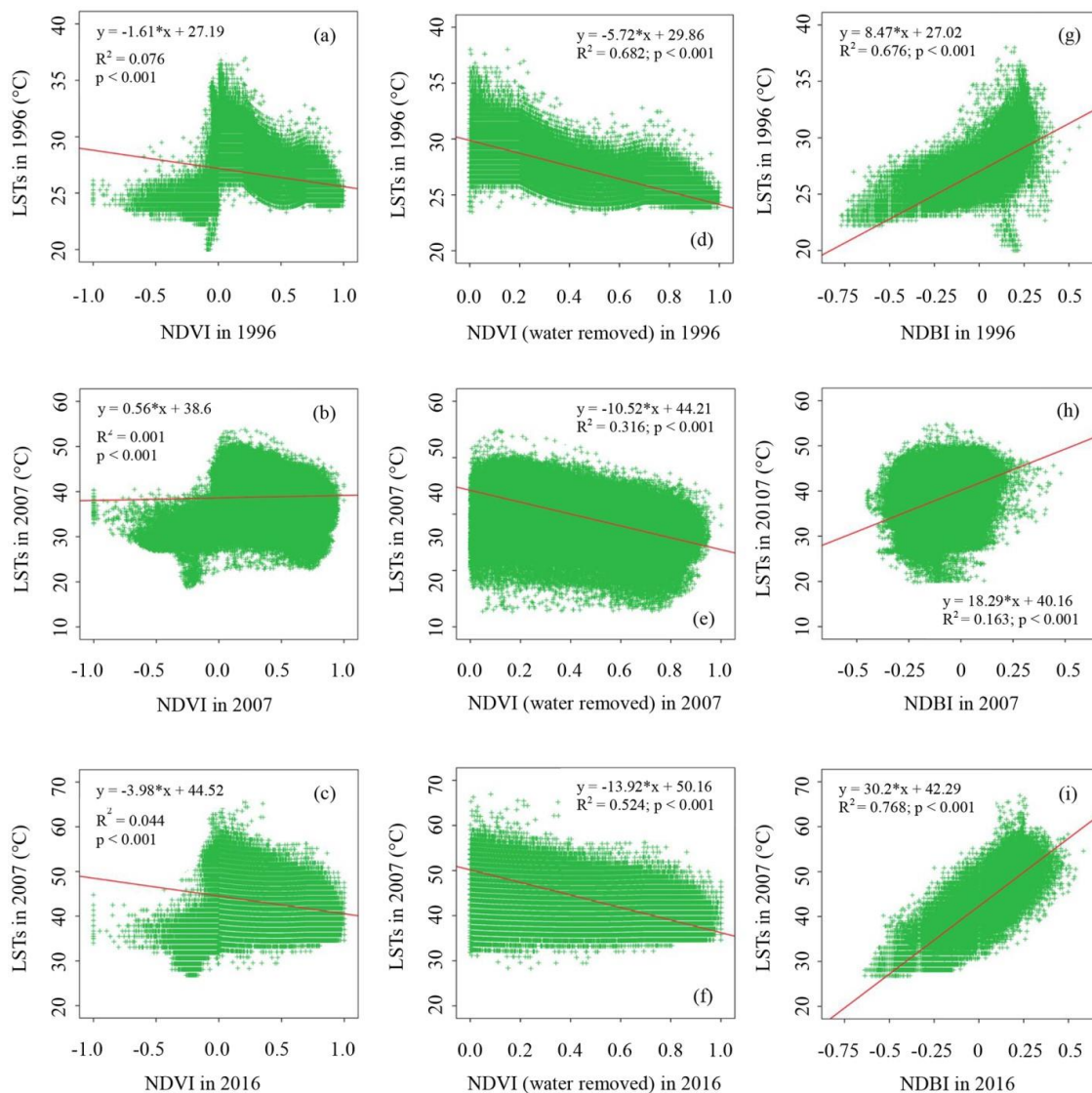


Figure 9. Scatter-plots of between LSTs and NDVI and NDBI

4. CONCLUSION

In this study, the effects of changes in vegetation and built-up land on LST was investigated based on multi-spectral Landsat-5 TM and Landsat-8 time-series images collected in summer in the HMA in the period of 1996-2016. LSTs were first retrieved by means of the RTM. Scatter-plots and the ULRM were then used to independently measure the influence of each NDVI and NDBI on LST, respectively. The MLRM was finally applied to improve the accuracy of the predicted model in the estimation of the joint effect of both of NDVI (vegetation) and NDBI (built-up land) on LST. It was found that (i) high LSTs and built-up land sprawl rate had been increasing along with the decrease of vegetation during 1996-2016 and tends to expand towards the western, north-western and south-western parts of the HMA; (ii) there exists a negative correlation between LST and vegetation,

whereas, a very strong positive correlation between LST and built-up land was also identified. The effect of changes in vegetation and built-up land on LST tend to increase rapidly in recent years. This result also indicated vegetation weakens the effect of UHIs, whereas the built-up land greatly strengthens the effects of UHIs in urban areas. These findings suggest that (i) LST, NDVI, NDBI and their spatio-temporal variations can be effectively derived from Landsat TM and OLI/TIRS data; (ii) the MLRM allows for the effective investigation of the joint-effects of both NDVI (vegetation) and NDBI (built-up land) on LST. Although this study revealed promising findings, further research is still required as some problems and difficulties have not been resolved in this study. For instance, other types of remotely sensed data acquired in winter need to be used instead of Landsat images which are not available.

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