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Evaluation of urban heat island based on the land surface temperature and spatial variables in Tabriz

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Abstract
In this study, the relationship between land surface temperature (LST) and spatial variables in Tabriz Metropolitan city was investigated using Land sat 8 OLI/TIRS images for summer and winter of 2018. For this, LST was calculated in accordance with the algorithm (Jimenez-Munoz& Sobrino, 2003) and proximity variables were prepared based on Distance Function in Arc GIS. According to the LST map obtained, down town area in Tabriz city experienced lower temperature than the suburban areas during day time. Some of the contributing factors such as population density, elevation, proximity to green space, could decrease the surface temperature, but on the other hand, the residential, industrial, religious and bare lands could increase the temperature in the city. Results of multiple linear regression analysis between LST and explanatory variables showed the model could estimate 63.7 % of the dependant variable in summer and 61.7% of it in winter. Based on the Beta, the results showed negative correlation between LST and some of the independent variables as, Population density, Elevation, proximity to green space, military and educational areas. Also, the one- way ANOVA test revealed that the difference between mean average temperature of various land use type were not significant

1. Introduction

One of the more serious impacts of urbanization is its effect on urban climate, especially the rise in urban temperature which called urban heat island (UHI) effect (Hirano & Fujita,2012). Increasing use of materials with high heat absorption and retention capacity, such as asphalt as well as thermal emissions derived from transport activities and industrial process intensify UHI effect (Jato-Espino,2019). UHI is a phenomenon whereby urban regions experience warmer temperatures than their rural surroundings (EPA, 2008). UHI influences well- being and welfare (Jato-Espino,2019), Average energy consumption (Rizwan et al., 2008; Hirano & Fujita,2012) and consequently, pollution (Li et al.,2018) and social equity of cities (Harlan et al.,2006). Many factors contribute to urban heat island formation, as time (day and season), synoptic weather (wind, cloud), city form (materials, geometry, greenspace), city function (energy use, water use, pollution), city size (linked to form and function), geographic location (climate, topography, rural surrounds) (Voogt & Oke, 2003). Due to its adverse impacts, significant research efforts have been performed to evaluate the urban heat island phenomenon's impact on the urban environment.

Takebayashi, Moriyama (2009), explored UHI mitigation effect achieved by converting to grass-covered parking, determined the air temperature reduce by the spread of grass-covered parking areas. Rajasekar and Weng (2009) also focused on the UHI monitoring and analysis using a non- parametric model: a case study of Indianapolis, highlighted the areas with maximum heat signatures have a strong correlation with impervious surfaces. Susca, Gaffin and DellOsso (2011), investigated the positive effects of vegetation: UHI and green roofs, found an average of 2ºc difference of temperature between the most and the least vegetated areas. Zhang, Yiyun, Qing, Jiang, (2012) in the study of UHI effect based on NDVI in the case of Wuhan city, showed that there is obvious negative correlation between NDVI and surface radiation and heating island strength is higher in industrial and commercial areas than others. Hathway and Sharples (2012) found that the urban form on the river bank influenced the levels of cooling felt away from the river bank. Peron, De Maria, Spinazze and Mazzali

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(2015), confirmed thermal impact of vegetation in the urban environment. Bokaei, kheirkhah Zarkesh, Daneshkar Arasteh and Hosseini (2016) showed negative correlation between land cover and LST. El-Hattab, Amany and Lamia (2018) found industrial buildings released a higher temperature than its surroundings and indicated that urban bare and semi bare land increased the UHI effect. Dwivedi and Krishna Mohan, (2018), recommended vertical walls and also dense urban vertical cover of forests to reduce the effect of UHI effect. Xiao et al., (2018) confirmed the cooling and humidifying effect of large green spaces was more obvious and stable. Jato-Espino (2018) highlighting the role of low reflectance of built- up surfaces in the UHI effect. Shirani-bidabadi et al, (2019) indicated that the areas which influenced by UHI are often in parts of Isfahan's city where vegetation cover is very sparse, the land is arid and industrialization and regional settlements are booming.

UHI literature has focused on explaining the UHI spatial pattern generally in summer based on explanatory variables, generally with 2D and 3D space factors. Among the explanatory variable's vegetation covers, water bodies play a key role in minimizing the UHI effect while urban bare and semi bare land, industrial and commercial zones maximizing the UHI effect.

According to the foregoing, the present study was carried out to follow two objectives: (1) the study of LST in Tabriz City using Landsat 8 OLI/ TIRS satellite image during the summer and winter of the year 2018, and, (2) using the parametric statistical method for analysing the spatial distribution of LST and its relationship with explanatory variables (Table. 8). To calculate LST, one of the widely used remote sensing methods that is based on thermal infrared wavelength was used (Jimenez-Munoz& Sobrino, 2003). The land use map prepared from the municipality land use map, and population distribution was also studied in the form of map prepared from the census in 2016.

2. Method

In this study, to evaluate the UHI and influenced area of the city, the satellite images of land sat 8 OLI/ TIRS (thermal band 10) were used the metadata of images were featured in Table 2.

In order to compute the LST, the thermal band digital number (DN) is numerically converted to radiometric scale using Eq. (1).

Eq. (1) is used for converting DN to radiance in Landsat 7 ETM image:

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{QCALMAX - QCALMIN}\right) * (QCAL - QCALMIN) + LMIN_\lambda \qquad (1)$$

Where,

L_λ= the cell value as the radiance
QCAL=digital number
$LMIN_\lambda$= spectral radiance scales to QCALMIN
$LMAX_\lambda$= spectral radiance scales to QCALMAX
QCALMIN=the minimum quantized calibrated pixel value (typically =1)
QCALMAX+ the maximum quantized calibrated pixel value (typically =255)
The value of $LMIN_\lambda$ and $LMAX_\lambda$extracted from the header file of landsat images are 0.10033 and 22.00180 respectively (Table.1)

Converting radiance to brightness temperature

After calculating spectral radiance (L_λ), the images were computed for their brightness temperature using either Planck's radiance function for temperature (Weng et al.,2004) or the approximation formula shown in Eq. (2).

$$T_{°C} = \frac{k_2}{Ln(\frac{k_1}{L} + 1)} - 273.15 \qquad (2)$$

Where T is the effective at sensor brightness temperature in Celsius, k_1 is calibration constant (in kelvin), k_2 is the calibration constant (Watts/$[m^2 * sr * \mu m]$), and Ln is the natural logharithem. Values of, $k_1$and k_2 for images are shown in Table 2

Table 1. Metadata of satellite image

Variable	description	value	Image. DATE_ACQUIRED	Scene center time
K1	Thermal Constants Band 10	774.8853		
K2		1321.0789	2018-08-09	07:31:48
Lmax	Maximum and minimum values of Radiance. Band 10	22.00180	2018-01-13	07:32:29
Lmin		0.10033		
QCALMAX	Maximum and minimum values of Quantize Calibration. Band 10	65535		
QCALMIN		1		
Oi	Orrection value. Band 10	0.29		

LST retrieved from each image of the studied period using the Eq. (3): (Weng & Lu, 2008).

$$LST = \frac{BT}{1 + W * \left(\frac{BT}{P}\right) * Ln(\varepsilon)} \qquad (3)$$

W is the effective band wave length (11.475 μm), $P = h * \frac{c}{s}(1.438 * 10^{2-} mK)$, h= Planck's constant, c= velocity of light, s= Boltzman constant $(1.38 * 10^{23-} j/k)$ and ε is land surface emissivity.

Land surface emissivity (ε) was estimated based on NDVI thresholds method as proposed by Sorbrino et al. (2004) as follows:
Normalized Differential Vegetation Index (NDVI) is calculated using the equation 4.

$$\text{NDVI} = \frac{(NIR - VIS)}{(NIR + VIS)} \qquad (4)$$

Where NIR and VIS are the near-infrared and visible light bands, respectively
If NDVI<0.15, then the pixel is considered as bare soil and the mean emissivity value used in this study was 0.97
if, NDVI>0.62

These kinds of pixels are considered as fully vegetated, and then a constant value for emissivity is assumed typically of 0.99

In the case of 0.15<NDVI<0.62
Is this case emissivity is calculated according to Eq. (5)

$$\varepsilon = \varepsilon_v P_v + \varepsilon_s(1 - P_v) \qquad (5)$$

Where ε_v is the vegetation emissivity and $\varepsilon_s$is the soil emissivity. P_v is the proportion of vegetation obtained according to Eq. (6) (Sobrino et al., 2004).

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} + NDVI_{min}}\right)^2 \qquad (6)$$

Where $NDVI_{max}$=0.62 and $NDVI_{min}$=0.15

In this context, the proximity was calculated based on Distance Function in Arc GIS for maximum distance of 150 m, and based on population density, elevation and building height, the urban blocks categorised into 5 different classes as in (Table. 2).

Table 2. Classes

Class	Building height (number of floors)	Elevation	Proximity(meter)	Population density	description
1	1-2	1400	30	100	Very low
2	3-4	1500	60	200	low
3	5-6	1600	90	300	moderate
4	7-8	1700	120	500	high
5	9-13	1800	150	500+	Very high

LST and explanatory variables were combined and because the continues nature of them the result was examined using parametric tests, for this purpose, the one-way analysis of variance (ANOVA) (Fisher, 1919) was used to explore the similarity between the samples belonging to each group.
Further investigation of possible influence of explanatory variables on LST has been explored by carrying out, Linear Regression Model. The linear regression model is estimated with Eq. (8):

$$LST = \alpha + \beta_1 X_1 + \beta_2 X_2 +, \ldots, +\beta_n X_n + \varepsilon \qquad (8)$$

3. Results

Fig.1 and Fig.2 demonstrate the LST maps. The surface temperature in winter varied between -5 ºc and 27 ºc at the time of imaging, the minimum temperature was -5 ºc related to urban constructed areas specially, residential, commercial and industrial land use type and the maximum temperature was 27 ºc related to urban bare lands in the study area. The maximum mean average of land surface was 18.61 ºc related to military sites.

And the surface temperature in summer varied between 10 ºc and 45 ºc at the time of imaging, the lowest average temperature was 24.5ºc related to urban constructed areas specially, settlement, commercial and industrial land use type and the maximum average temperature was 37.5 ºc recorded from transportation, military and urban bare lands in the study area. The mean average temperature of industrial areas was 34.5 ºc. for the imaging time in summer.

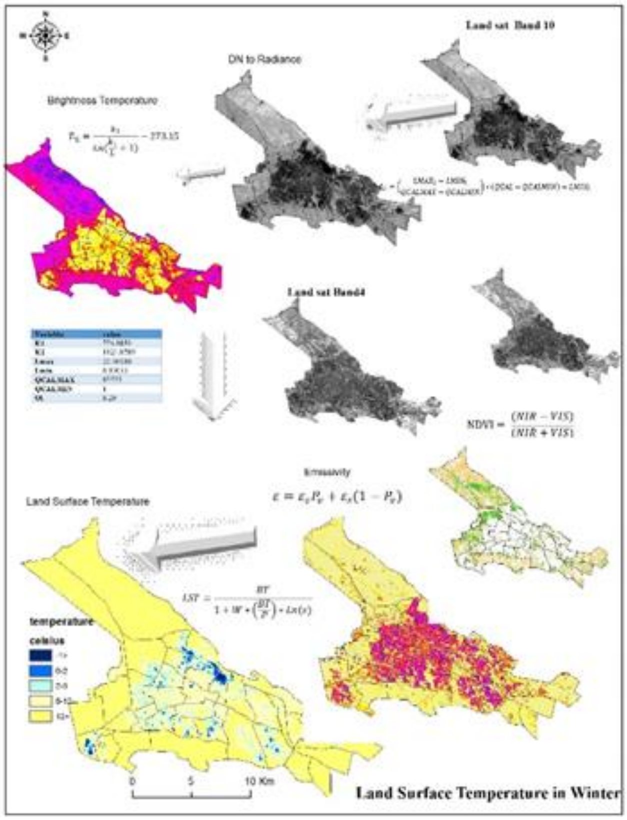

Fig.1. Land Surface Temperature of Tabriz in the 2018/01/13

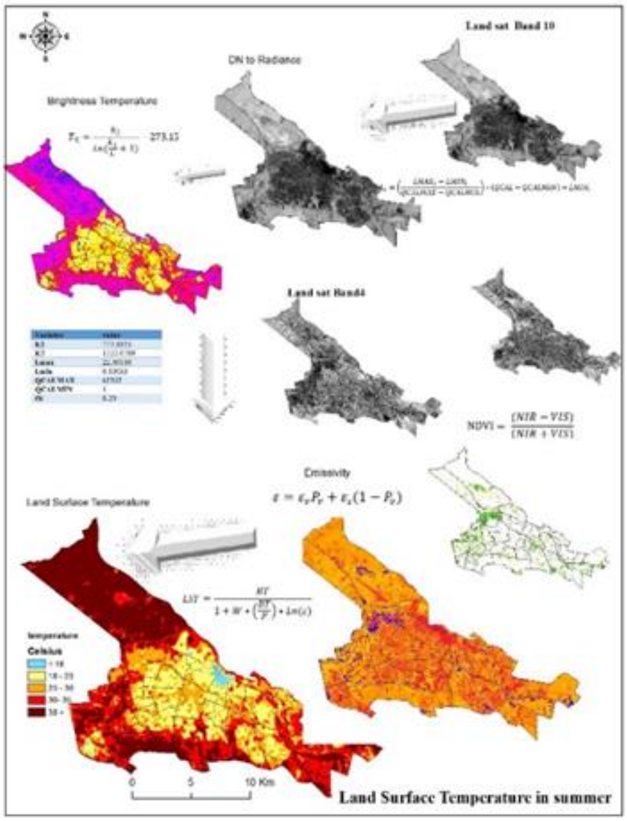

Fig.2. Land Surface Temperature of Tabriz in the 2018/08/09

Table. 3. One – way ANOVA analysis

Analysis	Land surface temperature				
	Population density	Proximity to green space	Land use type	Elevation	Building high
Sig between groups	0.00		0.001	0.00	0.00
F	190.352	7.891	2.288	21.713	14.283
	Reject H0	Reject H0	Reject H1	Reject H0	Reject H0

The out puts of One- Way ANOVA test (Table. 3) revealed that the difference between the groups were significant for all the variables except land use type.

Table 4. and Table 5 present the result of regression model for summer and winter time respectively.

Table 4. Model summery for summer time

Pearson Correlation

Model Summary

R	R Square	Adjusted R	B constant	T constant	F change	Df1	Df2	Sig. F change	Durbin Watson
0.798	0.637	0.637	34.438	0.637	7060.389	17	68384	.000	.297

Coefficients

	Elevation	Pop density	Building high	Green space	Military administr	Care	commercial	education	Residential	industrial	religious	river	Bare land	Sport	Facilities and equipmen	Tourism center	transport
B	-.006	-.006	-.008	-0.001	-0.002	0.002	0.001	0	0.008	0.002	0.001	0.000074	0.001	0.001	-0.001	-0.001	-0.002
Beta	-0.082	-0.243	-0.003	-0.044	-0.128	0.202	0.060	-0.010	0.405	0.119	0.146	0.014	0.032	0.108	0.071	0.064	-0.136
T	-27.70	-93.19	-1.05	-13.31	-38.13	45.68	9.98	-2.55	75.41	32.81	25.34	4.94	11.68	33.74	-28.69	-17.07	-44.58
sig	0.00	0.00	0.292	0.00	0.00	0.00	0.00	0.011	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5. Model summery for winter time

Pearson Correlation

Model Summary

R	R Square	Adjusted R	B constant	T constant	F change	Df1	Df2	Sig. F change	Durbin Watson
0.785	0.617	0.617	18.130	63.986	6479.193	17	68384	0	0.326

Coefficients

	Elevation	Pop density	Building high	Green space	administrative	Care	commercial	education	housing	industrial	religious	river	Bare land	Sport	Facilities and equipment	Tourism center	transport
B	-.006	-.006	0.001	-0.002	-0.003	-0.001	.002	0.002	-0.001	0.007	0.001	0.001	0	0.003	0.001	-0.001	-0.002
Beta	-0.092	-0.259	0	-0.131	-0.112	0.203	0.132	-0.043	0.415	0.005	0.161	0.050	0.077	0.108	-0.006	-0.121	-0.158
T	-29.96	-96.96	0.11	-38.81	-32.53	44.53	21.49	-10.38	75.11	22.78	27.06	-17.73	27.57	32.71	-24.54	-31.24	-50.41
sig	0.00	0.00	0.913	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

4. Discussion

The results of this study showed that the high temperature is most widespread in suburban areas especially in north west and south east rather than central parts of the city. Similarly, Shirani-bidabadi et al. (2019) suggested that down town area in Isfahan city experienced lower temperature than the suburban areas during day time. (Shirani-bidabadi et al. 2019; Georgescu et al., 2011; Lazzarini et al., 2015). Also, the same results were obtained by Lazzarini et al. (2015), highlighted that down town area in some other aried and semi-arid cities such as AbuDhabi, Kuwait City, Riyadh, Las Vegas, Phoenix, and Biskra experienced lower temperature than suburban areas during the day time. According to the results, the down town area of Tabriz in winter time experienced lower temperature than the suburban areas during day time, as well. This can be partly due to the existence of large number of bare lands in suburban areas (in the suburban areas of Tabriz) which mostly absorb sunlight than reflecting it and that leads to a higher temperature in suburbs than down town (Georgescu et al., 2011; Lazzarini et al., 2015). Because the imaging time is in early mooring, so there are not significant differences between the variance of mean average temperatures for different type of land use in the city, but on the other hand the difference among the different categories of population density, elevation, and proximity to green space (Table.3) are significant. According to the regression analysis, due to the status of urban structure mainly in the informal parts of the city with high elevation, the population density has negative effect on LST, which is different to Bokaei, et al, (2016) finding, suggested area with high temperature in the 14, 5,2,15,4 and 20 districts of Tehran face a high density of population. In the case of Tabriz, the relation between temperature and building high was not significant, and according the one –way ANOVA test the effect of the distance to green space on LST were significant, which is consistent with previous studies (Kolokotroni & Giridharan, 2008; Nastaran et al., 2019; Susca, Gaffin & DellOsso, 2011; Takebayashi & Moriyama, 2009),

El-Hattab et al., 2018, state that the high temperature was compatible with the distribution of industrial areas, industrial zones surface temperature is nearly 5 ºc higher than the center of Cairo, but the current study shows that differences between the variance of temperatures for different type of land use in the city is not significant. Rajasekar & Weng, 2009; suggested that the areas with maximum heat signatures have a strong correlation with impervious surfaces, similarly the current study highlighted the areas with maximum temperature related to transportation and bare lands.

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5. Conclusion

The research concerning influence of multiple variables on LST is set on a Tabriz city for two different time during 2018 in order to determine the general laws of LST in Tabriz regarding to the one- way ANOVA and multiple linear regression analysis. Due to the geographical position of the city and the imaging time, correlation between the selected variables is relatively strong which could estimate only 63.7 and 61.7 percent of the LST. The study is unique by its case study and statistical methodology comparing to the other studies. However, similarity to the previous studies some pattern between LST and proximity to different land use type, population density, building high, have been shown. in general, it could be said that the city has a low temperature than the suburban areas. The one –way ANOVA analysis of the various land use type indicate that the difference between temperature across the land use type not significant.

This study opens an opportunity and necessity for further research about the spatial pattern recognition of UHI and LST in Tabriz. There is need for more in-depth analysis of a selected city.

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