

URBAN GREEN SPACE ESTIMATION FOR HEAT HOTSPOT MITIGATION IN A SMALL CITY, BURIRAM MUNICIPALITY, THAILAND

Ekkaluk Salakkham and Pantip Piyatadsananon*

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Abstract

Heat hotspots cause environmental and health problems to residents in urban areas. Green space has been used to reduce the temperature in urban areas. However, the size and location of the green space that can reduce the temperature in those areas are challenging. This study aims to identify the heat hotspot of an urban area and estimate the green space proportion to reduce the heat hotspot. Therefore, the Split Window method (SW) was initially employed to calculate the Land Surface Temperature (LST) data from the Landsat series in the summertime of 2014, 2016, and 2018. The LST data 2018 were used in heat hotspot investigation using Moran's I and Getis-Ord G_i^* . The results show the clustering patterns of LST occurring in barren lands, racetracks, and built-up areas in Buriram Municipality. Then, the monthly regression modeling between the green space proportions and LST was analyzed and applied to the hotspot areas. The green space proportions were represented by estimating in regression models showing the ratio of green space and decreasing temperature in hotspot areas. As a result, the green space proportion around 45% of the area is suggested to mitigate the heat hotspot. The explored green space proportion was applied to the 2014 and 2016 data to assess the feasibility of hotspot mitigation. This research presents a simplified technic that will enable urban planners to estimate the green space proportion to reduce the heat hotspots effectively

Keywords: Land Surface Temperature, Split Window Technic, Hotspot Mitigation, Green Space, Landsat-8

Introduction

The Urban Heat Island (UHI) effect is a phenomenon causing air and surface temperatures in urban areas to be higher than in the surrounding rural areas (Bhargava *et al.*, 2017). However, the urban thermal environment varies not only from its rural surroundings but also within the urban area due to intra-urban differences in Land

Use and Land Cover (LULC) characteristics (Hart and Sailor, 2009).

Several studies assessed the UHI intensity by using in situ weather stations measuring air temperature in rural and urban sites: however, the stations, unevenly distributed, do not permit a global view over the study area (Keeratikasikorn and

School of Geoinformatics, Institute of Science, Suranaree University of Technology, University Avenue Muang District, Nakhon Ratchasima, 30000, Thailand. E-mail: aekkarak.sk@bru.ac.th; pantip.p@sut.ac.th

* Corresponding author

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Bonafoni, 2018). Satellites are an invaluable tool for UHI studies because of their ability to detect the thermal features of the Earth's surface with a broad spatial resolution (Streutker, 2002; Arnfield, 2003; Hung *et al.*, 2006). A study by Piyatadsananon and Salakkham (2022) showed that the Split Window technic (SW) result was more accurate than the others in a small city such as Buriram Municipality, Thailand. The SW technic considers two thermal infrared channels, which can capture more acceptable land surface information.

High-temperature environments negatively impact human health and comfort (Stewart and Oke, 2012) and increase cardiovascular and respiratory diseases (Tian *et al.*, 2013; Vaneckova *et al.*, 2008). Therefore, identifying the hotspots prioritizes areas for a heat mitigation and adaptation plan (Adeyeri *et al.*, 2017). Based on previous studies, Ren *et al.* (2016) used the Getis-Ord G_i^* statistic to detect the spatial position of hot and cool spot clustering areas of the Land Surface Temperature (LST) in urban forests to determine the threshold distance scale. Furthermore, they studied the human activities associated with the ecological factors influencing the LST in clustering regions of urban forests. Feyisa *et al.* (2016) also used the Getis-Ord G_i^* to explore the thermal aggregation in different city areas and examine the thermal variations between urban and rural landscapes. The implementation of the Getis-Ord G_i^* to investigate the Surface Urban Heat Island (SUHI) effect was limited to the hotspot and cool spot identification. Adeyeri *et al.* (2017) identified the hotspot areas using the Getis-Ord G_i^* and investigated the SUHI characteristics in Abuja, Nigeria. Significant hotspots of high LST were presented in built-up areas and bare surfaces, while significant cold spots were found over vegetation. Furthermore, Tran *et al.* (2017) assessed the impacts of the LULC change and urbanization on the UHI using hotspot analysis (Getis-Ord G_i^* statistics) and urban landscape analysis.

Humans have attempted to modify the environment to reduce to heat to live comfortably in cities. Many researchers have considered using a wind tunnel concept, high albedo materials, and increasing the wetlands and green spaces. The most effective landscape strategy to reduce the UHI problem is vegetation (Vidrih and Medved, 2013). This concept addresses the real cause of the problem (Dimoudi and Nikolopoulou, 2003; Stabler *et al.*, 2005) and reduces the heat stress produced by UHIs (Lin *et al.*, 2011). Furthermore, urban green

space also provides other ecosystem services, such as biodiversity habitats (Norton *et al.*, 2015). Based on previous studies, it was found that a ten percent increase in green space cover can reduce the LST by 0.86°C (Li *et al.*, 2012). It was also found that the temperature dropped by 0.02°C for every percentage increase in tree canopy cover (Feyisa *et al.*, 2014). Therefore, it was confirmed that an increase in vegetation cover or an increase in the number of green spaces could reduce the air and surface temperature (Kuo, 2000; Dimoudi and Nikolopoulou, 2003; Giridharan *et al.*, 2008; Li *et al.*, 2012; Kong *et al.*, 2014).

However, the green spaces in cities exist mainly as semi-natural areas, managed parks and gardens, supplemented with scattered vegetated pockets associated with roads and incidental locations (Jim and Chen, 2003). Furthermore, current knowledge on the effects of urban vegetation and green spaces on LST is not comprehensive as it ignores the possible influence of landscape pattern and spatial configuration of vegetation patches, especially the size of green space used in hotspot mitigation (Kowe *et al.*, 2021). As it was addressed, the size of vegetation patches influences the cooling effect in the hotspot area. Therefore, the sizes of green space required to reduce the heat hotspot areas are a challenge of this study. In order to achieve this aim, LST needs to be firstly estimated by using the SW method on the Landsat series in the summertime of the study area. Secondly, heat hotspots generated from the LST must be identified over the study area. Lastly, a regression model is employed to estimate the ratio of green space related to the heat hotspot location and size.

Materials and Methods

Study Area

Buriram town municipality (as shown in Figure 1.) is a small city in Buriram province, Thailand. The town municipality area is approximately six square kilometers (Buriram Municipality, 2022). It is the most crowded town municipality in the northeastern region of Thailand (4,328 people per square kilometer) (The Bureau of Registration Administration, 2018). Buriram town municipality and adjacent areas have encountered urbanization due to the successful annual sports activities and expos supported by the government and political parties (Buriram World, 2017; Tourism Authority of Thailand, 2017).

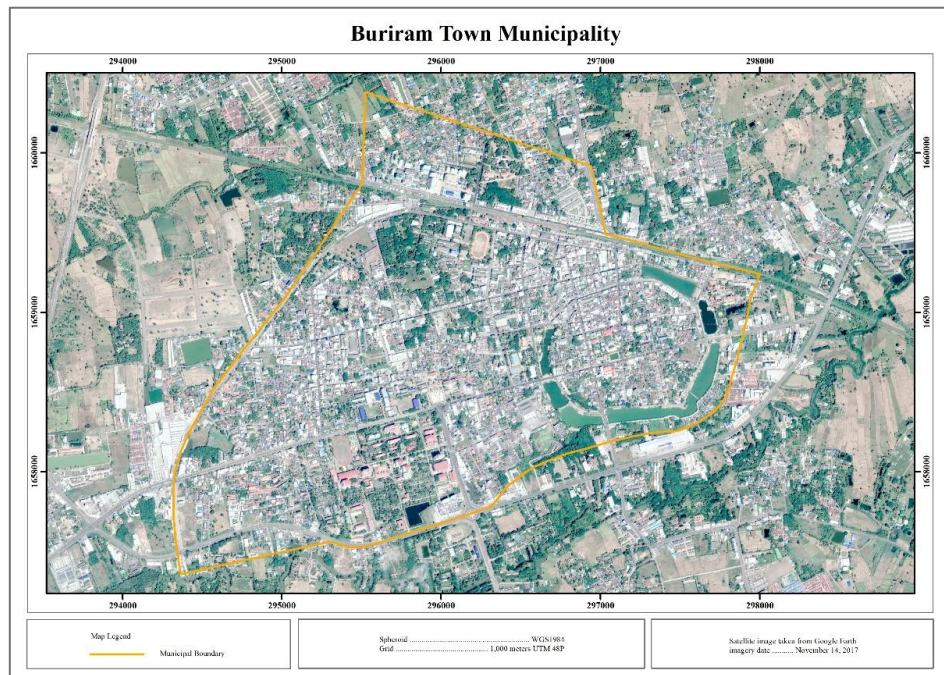


Figure 1. Study Area, Buriram Town Municipality, Buriram province, Thailand

Table 1. Data used in the study

Data	Date	Sources
Landsat-8 data; Path /Row: 128 /50	20 March and 5 April 2014, 31 March and 16 April 2016, 21 January, 6 February, 26 March, 11 April 2018	U.S. Geological Survey (USGS)
Ground-based temperature data	21 January, 6 February, 26 March, 11 April 2018	In situ survey between 10 and 11 A.M.
UAV image (GSD = 5 cm)	March–April 2018	In situ survey

Table 2. Atmospheric parameters used in the LST estimations (from Huai Rat Station, the nearest station to Buriram Town Municipality).

	21 January	6 February	26 March	11 April
Air Temperature (T_0) ($^{\circ}\text{C}$)	30.75	19.95	29.75	36.15
Relative Humidity	0.63	0.60	0.65	0.44
Water Vapor Content	2.86	1.52	2.79	2.72

Data

Remote sensing images, Landsat-8 images from 31 March and 5 April 2014, 20 March and 16 April 2016, 21 January, 6 February, 26 March, and 11 April 2018, were used for the LST estimation in this study. The LST data in 2018 were used in hotspot identification and estimated the green space proportion, which can mitigate the hotspot area. On the other hand, the LST data in 2014 and 2016 were used to assess the feasibility of the results, green space proportion, in hotspot mitigation. The in situ LST surveying was measured by a handheld infrared camera (FLIR E60 incl. Wi-Fi) on 21 January, 6 February, 26 March, and 11 April 2018 at the exact dates and times of the Landsat-8 data acquisition. Then, the in situ LST data and the

estimated LST based on Landsat data 2018 were compared using Normalized Root Mean Square Error (NRMSE). The Unmanned Aerial Vehicle (UAV) images (five cm. Ground Sample Distance (GSD)) taken from March to April 2018 were used for the LULC classification. The buildings, roads, and green space were interpreted visually from a very high-resolution image from UAV. Therefore, the green space proportions in study sites were identified accurately on the UAV image. The LST data and LULC data in 2018 were used in regression modeling to explore the green space proportion used in hotspot mitigation. The data used in this study are shown in Table 1. The atmospheric parameters used in the SW method are listed in Table 2.

LST Estimation and Accuracy Assessment

This study used the SW method to calculate the LST based on the Landsat-8 data of Buriram municipality. This research selected the LST data from January to April 2018 as a case study. Based on the analysis of Piyatadsananon and Salakkham (2022), it was found that the SW method showed a more complex surface and provided the most accurate LST calculation over others, such as the Radiative Transfer Equation-based method (RTE), the Improved Mono-Window method (IMW), and the Generalized Single-Channel method (GSC) in Buriram municipality. The SW algorithm developed by Jimenez-Munoz *et al.* (2014) is used in this study, as shown in Equation (1):

$$T_s = T_i + C_1(T_i - T_j) + C_2(T_i - T_j)^2 + C_0 + (C_3 + C_4w)(1 - \varepsilon) + (C_5 + C_6w) \Delta\varepsilon, \quad (1)$$

where C_0 to C_6 are the SW coefficients, T_i and T_j are the at-sensor brightness temperature of bands i and j , respectively, ε is the land surface emissivity obtained from $\varepsilon = 0.5 (\varepsilon_i + \varepsilon_j)$, and $\Delta\varepsilon = (\varepsilon_i - \varepsilon_j)$ and w is water vapor content.

A handheld digital thermometer was calibrated before measuring the LST in the sample sites. One hundred sample sites (as shown in Figure 2.) were measured, and we recorded the LST in the center of the Landsat-8 pixel, 100 × 100 m of thermal bands, between 10 and 11 A.M. on 21 January, 6 February, 26 March, and 11 April 2018.

The sample sites were chosen by delineating 100×100 m. grids over the image pixels. Then, stratified random was used to select the locations of sample sites related to the LULC types. Definitely, the large area of some LULC types will have more sample sites.

The NRMSE values were calculated from the temperature generated by calculating the thermal bands of the Landsat-8 compared with the ground survey temperature from the handheld digital thermometers as Equation (2):

$$NRMSE = \frac{RMSE}{\text{Maximum observation} - \text{minimum observation}} \quad (2)$$

Where RMSE is root mean square error, which is calculated based on Equation (3):

$$RMSE = \sqrt{\frac{1}{2} \sum (\text{estimate value} - \text{observe value})^2} \quad (3)$$

Hotspot Identification

The significance of hotspot analysis is capable to allow statistical-based estimation of spatial variation in thermal aggregation (Feyisa *et al.*, 2016). Spatial autocorrelation analysis categorized as global and local spatial association measures can provide a statistical result from the identified hotspots with a significance value. Karlstrom and Ceccato (2002) indicated that the global measurement of spatial association provides a tool for proving the cluster of spatial patterns over

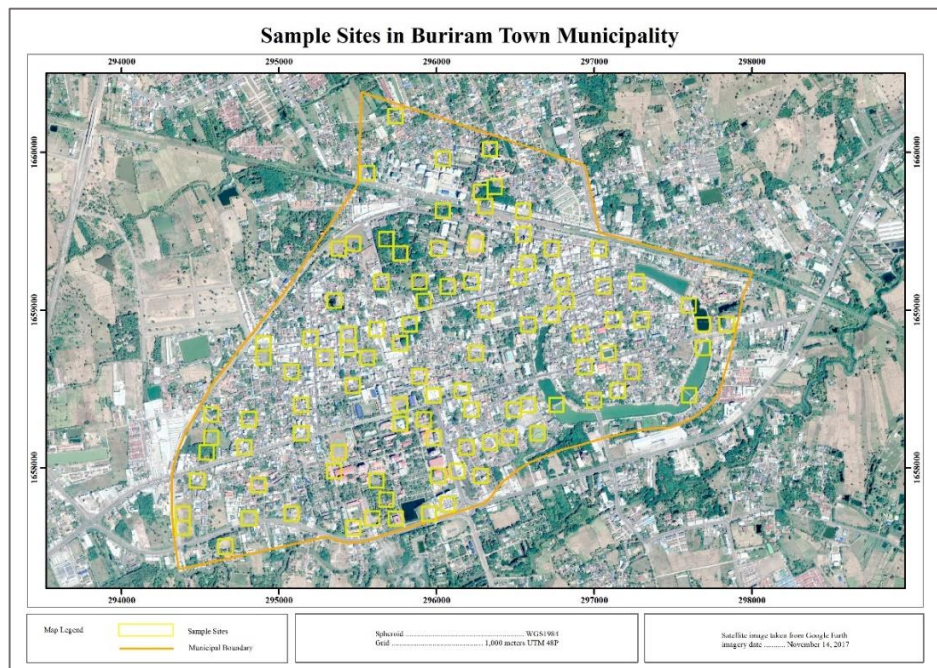


Figure 2. Sample sites and locations in the study area

a whole study area. The Moran's Index (Moran's I) can be used for a global measure of correlation among neighboring observations in the patterns, such as cluster, dispersion, and randomness (Boots and Getis, 1998).

The Global Moran's I is an inferential statistic in which the results are always interpreted within the null hypothesis. The null hypothesis states that the data are randomly distributed; when the Z-score is significant (or small) enough and falls outside the desired significance, the null hypothesis is rejected. A Moran's Index value near +1.0 indicates a clustering pattern, while an index value near -1.0 indicates a dispersion pattern (Prasannakumar *et al.*, 2011; ESRI, 2022).

On the other hand, the local Getis-Ord G_i^* statistic provides a criterion for identifying clusters of high or low values, indicating the presence of significant local spatial clusters (Karlstrom and Ceccato, 2002). This technic has long been used to characterize the presence of hotspots (high clustered values) and cold spots (low clustered values) over an entire area by looking at each feature (LST value) within the context of the proximity features (Ord and Getis, 1995).

Wang *et al.* (2015) indicated that a statistically significant positive Z-score whether a higher value is a high-value spatial agglomeration (hotspot area). In contrast, for statistically significant negative Z-scores, the value is closer to the low value (cold spot) clustering indicating the location of values around i is relatively low (below average), where i belongs to a low-value spatial agglomeration (cold spot area). The LST hotspots were analyzed in this research, with significant levels of 0.10, 0.05, and 0.01, respectively. Therefore, all hotspots that occurred from January to April 2018 were identified to present the existing hotspot locations.

Hotspot Mitigation by Considering Green Space

This study was designed to present the integration technic between remote sensing data and statistical technic to investigate the optimal green space proportion, which can reduce the heat hotspot temperature to near or equal to the surrounding area temperature. Green spaces were considered to mitigate the heat concentrations in urban areas effectively (Li *et al.*, 2012, Feyisa *et al.*, 2014). For this reason, the differentiated temperature between the maximum temperature in the hotspot area and the maximum

Temperature in the surrounding area of each month were first calculated. These differentiated temperatures were considered at least decreased temperature to reduce the hotspot temperature to near or equal to the surrounding area temperature.

Then, the relationships between monthly LST data in 2018 and green space proportions from

sample points were determined using regression analysis. Seventy percent of the data were randomly selected and used in regression modeling, while the rest thirty percent were used in the regression models' accuracy assessment by considering RMSE values.

The different green space proportions were used in regression models to estimate the LST data. The green space proportions which can reduce the heat hotspot temperature equal or higher than the at least decreased temperature in all months was selected as the optimal green space proportion in hotspot mitigation.

Lastly, the optimal green space proportions used in hotspot mitigation in 2018 was applied to the 2014 and 2016 data. The Landsat-8 images obtained between March and April 2014 and 2016 extracted the LST data using the SW method. Then, the regression models between monthly LST data and green space proportions from sample points were analyzed. The differentiated temperature between the maximum temperature in each month's temperature and the surrounding area was also calculated and used as the at least decreased temperature. The monthly regression models were applied with the selected green space proportion to estimate the LST data. If the estimated LST is equal to or higher than the at least decreased temperature, it indicates that the selected green space proportion can mitigate the hotspot area.

Results and Discussion

LST Estimation and Accuracy Assessment

The results from the SW technic show a complex LST in Buriram municipality, as shown in Figure 3. It can be seen that the cold spots occur in the North-West and South-East area of the city, where are urban forests and wetlands. In contrast, the areas with high temperatures are in the bare land and built-up area, where are most of the city.

As a result, the NRMSE values between the LST generated from the SW technic and ground temperature measurements are listed in Table 3.

The highest NRMSE was found in February (0.473), followed by January (0.227), March (0.218), and April (0.132), respectively. The overall NRMSE was around 0.114. Considering the weather on 6 February, inclement weather appeared, in which the average temperature dropped significantly compared with others in the summertime (see more details in Table 2). Therefore, it might relate to the highest NRMSE in February. Therefore, the SW technic can be used finely to calculate the LST from the Landsat-8 data on the day without inclement weather conditions.

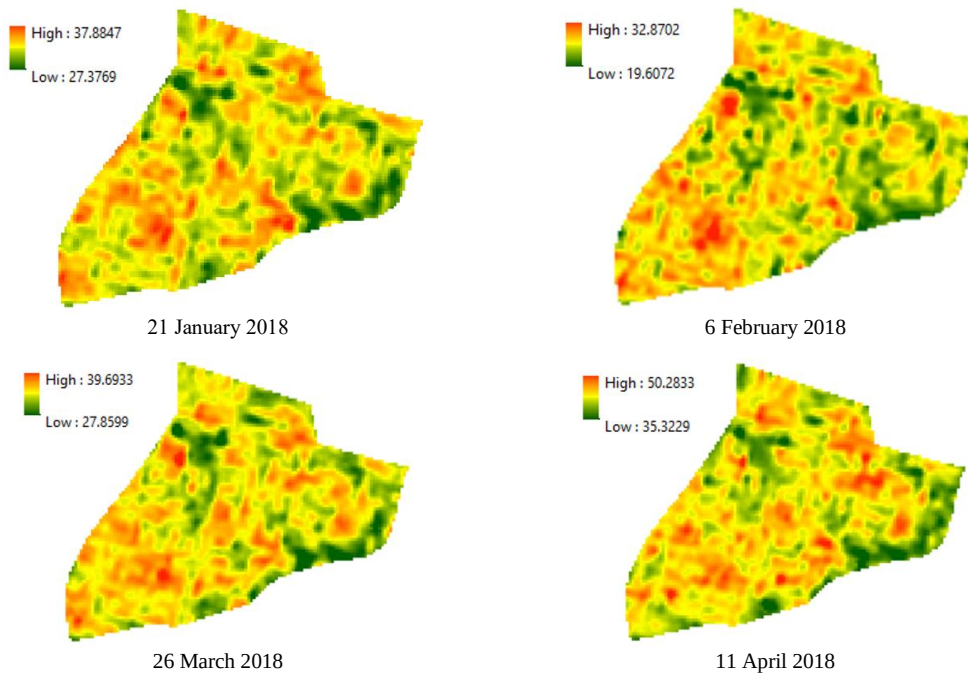


Figure 3. LST maps were generated from January to April 2018 using Landsat-8 data

Table 3. NRMSE values of the LST from the SW and ground survey data

Date	NRMSE
21 January 2018	0.227
6 February 2018	0.473
26 March 2018	0.218
11 April 2018	0.132
Overall NRMSE	0.114

This study employed satellite images from free available data of the Landsat series concerning the missions for diverse government organizations with affordability. Therefore, the SW is an appropriate algorithm for LST calculation in this study. Moreover, the Landsat mission was applicable for monitoring the LST regularly since the data are freely available and consistently obtainable. Several Landsat series have been utilized for local-scale studies of the UHI effect (Weng, 2001; Yuan and Bauer, 2007; Kumar *et al.*, 2012; Lauwaet *et al.*, 2016). Although the spatial and spectral thermal resolution is suitable for global coverage, it was detailed enough to monitor the dynamics of local weather conditions and urban expansion (Masek *et al.*, 2000). It was confirmed by many studies, Nichol and Wong (2008); Sun *et al.*, (2012); Weng, (2009); Weng and Quattrochi (2006), that the calculated LST values were close to atmospheric temperatures due to the transference of energy emitted from the land surface to the atmosphere. This study, therefore, used the LST

values calculated by the SW method to generate the LST over the study area. The percentage of cloudiness is another significant parameter in selecting the image for this study. The lowest percentage of cloudiness was considered presenting January to April 2018 as suitable for the study. However, February 2018 showed the inclement weather. This phenomenon presented the highest NRMSE (0.473), as shown in Table 3. Therefore, it can be concluded that the accuracy of this method is based on the weather conditions, especially the amount of atmospheric water vapor content data, as confirmed by a study by Piyatadsananon and Salakkham (2022). Like Buriram municipality, a small and dense city with plenty of built-up areas can reflect a high LST with various water vapor content data in the summertime. The available weather data for this study was derived from a local weather station close to the study area. It is suggested that the local weather station in the municipality is preferred to calculate LST results.

Identifying Hotspot Areas from the LST Data

The results of Moran's I method, which was used to explore the LST patterns, are shown in Table 4, followed by the hotspot patterns from January to April 2018. The highest Z-score was found in March 2018 at 55.903, followed by a Z-score in April and February 2018 at 55.197 and 55.185, respectively. The highest Moran's Index was found in March 2018 at 0.927; on the other hand, other months showed the Moran's Index as

0.915. Based on the results, all months showed Z-scores larger than 1.65, 1.96, and 2.58. Moreover, the p -values were less than 0.10, 0.05, and 0.01 at 90, 95, and 99 percent confidence levels. Therefore, it can be concluded that the data patterns were clustered.

Table 4. Moran's I result

Date	Z-Score	Moran's Index	Pattern
21 January 2018	55.184	0.915	Cluster
6 February 2018	55.185	0.915	Cluster
26 March 2018	55.903	0.927	Cluster
11 April 2018	55.197	0.915	Cluster

As a result, these data can identify the hotspot areas that occurred during this period using Getis-ord Gi*. Based on the very-high-resolution image of a UAV taken in March to April 2018 (Figure 4), it presents the boundary of Buriram municipality in an orange polygon with a scattering of sixteen hotspots in yellow grids. The hotspot areas occurred in bare land, racetracks, and built-up areas. The barren lands are shown as location numbers, 6, 8, 9, and 13. However, the areas were not only bare land, as some parts were covered with dry grass. The only part of location number 13 was bare land, used as the parking lot. The racetracks are shown as location numbers 15 and 11. Lastly, the hotspot areas occurred in built-up residential, commercial,

educational, and government institution areas. The residential areas are shown as location numbers 4, 7, 10, 14, 16, and part of 13. The commercial areas are shown as location number 1, 2, and 3. A part of the educational institution area is shown as location number 12, where there was construction, a parking lot at Buriram Rajabhat University, and a nearby parking lot. Finally, the government institutions are shown as location number 5 (hospital) and some as location number 13.

The average high temperature appears in commercial areas and areas with a high density of buildings and road networks, same as the conclusion of many studies (Xu *et al.*, 2009; Van and Bao 2010; Cai *et al.*, 2011; Li *et al.*, 2011; Rinner and Hussain, 2011; Dobrovolny, 2013). It was confirmed that the LST of built-up lands is higher than the natural-cover lands, same as the conclusion of Xu (2010).

With the benefit of the very-high-resolution image from UAV, it provides magnified details of each grid in a hotspot location that is useful to study the composition of land-cover types and the represented surface temperature of the hotspot location (shown in Figure 5). This study selected hotspot location number 1 (Figure 4) to estimate the green space proportion for hotspot mitigation. This area contains the most intensive activities without green space coverage compared to other hotspot areas. It covers some parts of the market and some of the commercial zones in the municipality.

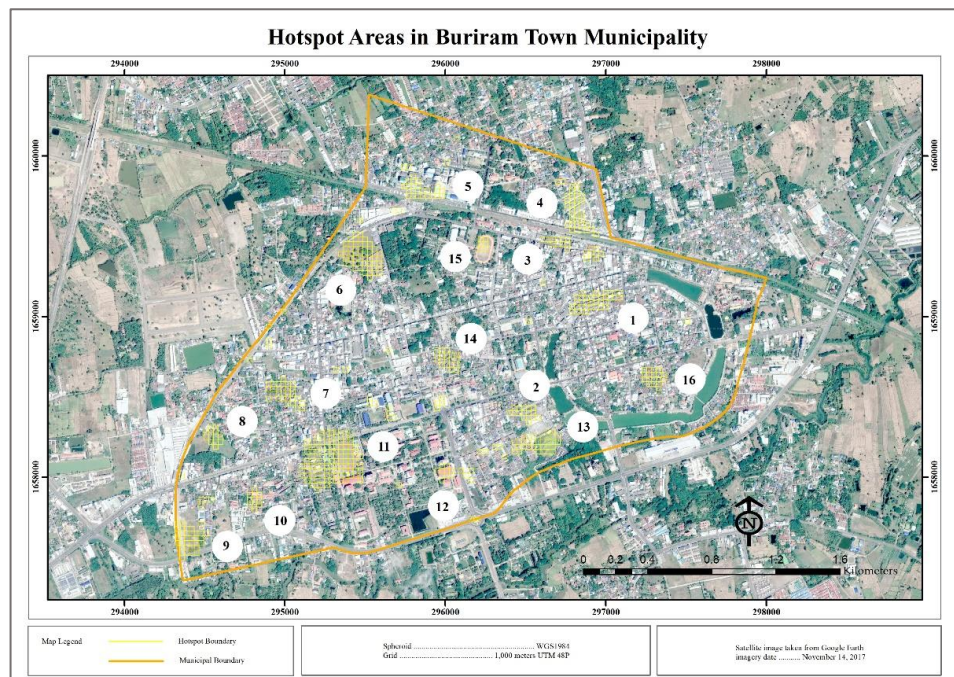


Figure 4. Hotspot areas, shown as yellow grids, in 2018



Figure 5. The selected hotspot area: location number 1, is shown as a red box on the index map

Note: The number and letter next to the red grids of the map are used for identifying the grid positions. A Small map in the corner of the map is an index of the overall study area.

Table 5. The differentiated temperature (°C) of hotspot location number 1

	2018			
	January	February	March	April
Minimum Temperature in hotspot (°C)	34.35	28.70	35.35	47.80
Maximum Temperature in hotspot (°C)	36.29	31.26	37.36	49.12
Average Temperature in hotspot (°C)	35.34	29.77	36.57	48.33
Surrounding Maximum Temperature (°C)	35.79	30.17	37.00	47.59
Differentiated (Hotspot-Surrounding Maximum Temperature) (°C)	0.50	1.09	0.36	1.53

The average, minimum, and maximum temperatures in the hotspot and surrounding areas are listed in Table 5.

Considering the grid map of the hotspot, location number 1 consists of different LULC types, which can be classified and listed in Table 6. The total green spaces, buildings, and roads were 0.00, 23,123.30, and 7,476.70 square meters in hotspot location number 1. The proportions of the LULC were 0.00, 0.76, and 0.24, respectively. Generally, heat hotspot mitigation aims to reduce the temperature in hotspot areas to nearly or equal the surrounding areas. The reduced temperature was calculated based on the differentiated temperature between the maximum temperature in the hotspot area and the maximum temperature in the surrounding region. As the results, the differentiated temperatures between the maximum temperatures in

the hotspot location number 1 and its surrounding areas in January, February, March, and April 2018, regarding Table 5, were 0.50, 1.09, 0.36, and 1.53°C, respectively. Therefore, the green space proportions, which could decrease the hotspot temperature by around 0.50-2.00°C, were determined in this section.

The Green Space Proportions Used in Hotspot Mitigation

The regression models between green space proportions and LST data are shown in Table 7. The correlation between green space proportions and LST data are correlated significantly (R^2 from 0.611 to 0.821), while the lowest correlation appears on 6 February 2018 ($R^2 = 0.494$) due to the wide range of differences between maximum temperature and surrounding temperatures of this month.

Table 6. LULC in the hotspot location number 1

Grid	Areas (Square Meters)				Proportions of LULC			
	TR	BU	RD	Total	TR	BU	RD	Total
1D	-	440.30	459.70	900.00	0.00	0.49	0.51	1.00
1E	-	594.82	305.18	900.00	0.00	0.66	0.34	1.00
2B	-	582.75	317.25	900.00	0.00	0.65	0.35	1.00
2C	-	376.06	523.94	900.00	0.00	0.42	0.58	1.00
2D	-	754.62	145.38	900.00	0.00	0.84	0.16	1.00
2E	-	806.20	93.80	900.00	0.00	0.90	0.10	1.00
3A	-	854.52	45.48	900.00	0.00	0.95	0.05	1.00
3B	-	898.13	1.87	900.00	0.00	1.00	0.00	1.00
3C	-	496.87	403.13	900.00	0.00	0.55	0.45	1.00
3D	-	569.48	330.52	900.00	0.00	0.63	0.37	1.00
3E	-	549.10	350.90	900.00	0.00	0.61	0.39	1.00
4B	-	704.79	195.21	900.00	0.00	0.78	0.22	1.00
4C	-	526.26	373.74	900.00	0.00	0.58	0.42	1.00
4D	-	900.00	-	900.00	0.00	1.00	0.00	1.00
4E	-	900.00	-	900.00	0.00	1.00	0.00	1.00
5B	-	626.65	273.35	900.00	0.00	0.70	0.30	1.00
5C	-	726.87	173.13	900.00	0.00	0.81	0.19	1.00
5D	-	900.00	-	900.00	0.00	1.00	0.00	1.00
6A	-	748.52	151.48	900.00	0.00	0.83	0.17	1.00
6B	-	576.90	323.09	900.00	0.00	0.64	0.36	1.00
6C	-	900.00	-	900.00	0.00	1.00	0.00	1.00
6D	-	900.00	-	900.00	0.00	1.00	0.00	1.00
7B	-	473.52	426.48	900.00	0.00	0.53	0.47	1.00
7C	-	797.27	102.73	900.00	0.00	0.89	0.11	1.00
7D	-	863.93	36.08	900.00	0.00	0.96	0.04	1.00
8A	-	446.02	453.98	900.00	0.00	0.50	0.50	1.00
8B	-	658.76	241.24	900.00	0.00	0.73	0.27	1.00
8C	-	900.00	-	900.00	0.00	1.00	0.00	1.00
8D	-	812.93	87.07	900.00	0.00	0.90	0.10	1.00
9A	-	406.44	493.56	900.00	0.00	0.45	0.55	1.00
9B	-	691.42	208.58	900.00	0.00	0.77	0.23	1.00
10B	-	746.14	153.86	900.00	0.00	0.83	0.17	1.00
11A	-	378.05	521.95	900.00	0.00	0.42	0.58	1.00
11B	-	615.98	284.02	900.00	0.00	0.68	0.32	1.00
Total	-	23,123.30	7476.70	30,600	0.00	0.76	0.24	1.00

Note: TR is the tree, BU is the built-up area, and RD is the road.

Table 7. The regression statistics.

Data	R	R ²	Adjusted R ²	Equation	RMSE (°C)
31 March 2014	0.891	0.793	0.792	44.347 - 3.683 [TR]	1.085
16 April 2014	0.906	0.821	0.820	40.501 - 4.631 [TR]	1.274
20 March 2016	0.819	0.671	0.670	41.538 - 1.212 [TR]	0.998
5 April 2016	0.894	0.799	0.798	44.152 - 3.007 [TR]	1.113
21 January 2018	0.782	0.611	0.611	34.833 - 2.428 [TR]	0.965
6 February 2018	0.708	0.494	0.493	29.594 - 1.551 [TR]	0.906
26 March 2018	0.877	0.769	0.768	35.851 - 2.623 [TR]	0.998
11 April 2018	0.848	0.719	0.718	46.195 - 4.310 [TR]	1.404

Note: TR represents the green space proportion.

As a result, listed in Table 5, shows that reducing the hotspot temperature by 0.50-2.0°C could make its temperature close to the surrounding areas. Therefore, green space proportions were estimated to reduce the hotspot temperature as expected results in a sample site, hotspot location number 1. The proportions of green space were set as 15%, 30%, 45%, and 60% of the total hotspot area, which were converted to 0.15, 0.30, 0.45, and 0.60 for the calculation. The green space proportions and the decreased hotspot temperature are in Table 8.

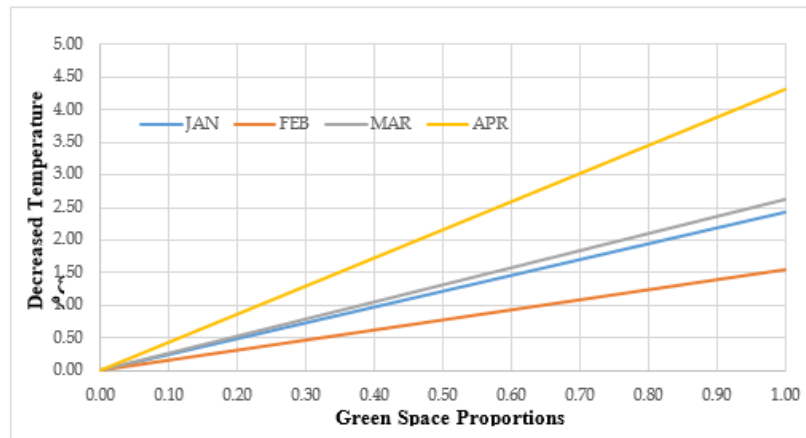
Based on Table 8, a green space proportion around 0.15 of the area would only decrease

the hotspot temperature on 26 March 2018. A proportion of green space around 0.30 was needed to reduce the hotspot temperature on 21 January and 26 March 2018. However, to decrease the hotspot temperature more than the minimum on 21 January, 26 March, and 11 April 2018, a proportion of green space around 0.45 of the area was needed. With the proportion of green space increased to 0.60 of the area, the decreased temperature on 6 February 2018 was lower than the minimum decrease in temperature with a differentiated temperature of around 0.16°C.

Table 8. Decreased temperature based on the different green space proportions at hotspot location 1 (°C)

Green Space Proportions		21 January 2018		6 February 2018		26 March 2018		11 April 2018	
		Decreased Temperature (°C)	ΔT (°C)	Decreased Temperature (°C)	ΔT (°C)	Decreased Temperature (°C)	ΔT (°C)	Decreased Temperature (°C)	ΔT (°C)
0.15	Min	33.98	0.36	28.47	0.23	34.96	0.39	47.16	0.65
	Max	35.93	0.36	31.02	0.23	36.97	0.39	48.48	0.65
	Mean	34.98	0.36	29.54	0.23	36.18	0.39	47.68	0.65
0.30	Min	33.62	0.73	28.23	0.47	34.56	0.79	46.51	1.29
	Max	35.57	0.73	30.79	0.47	36.57	0.79	47.83	1.29
	Mean	34.62	0.73	29.30	0.47	35.78	0.79	47.04	1.29
0.45	Min	33.25	1.09	28.00	0.70	34.17	1.18	45.86	1.94
	Max	35.20	1.09	30.56	0.70	36.18	1.18	47.18	1.94
	Mean	34.25	1.09	29.07	0.70	35.39	1.18	46.39	1.94
0.60	Min	32.89	1.46	27.77	0.93	33.78	1.57	45.22	2.59
	Max	34.84	1.46	30.33	0.93	35.79	1.57	46.54	2.59
	Mean	33.89	1.46	28.84	0.93	35.00	1.57	45.74	2.59

Note: ΔT is the differentiated temperature between the actual temperature and the decreased temperature.

**Figure 6.** Decreased temperature is related to the green space proportions

From these findings, the green space proportion of 0.45 of the area was the minimum proportion required to mitigate the hotspot temperature. Considering the hottest month, April, the temperature can decrease more rapidly than in the colder month, February. The green space proportion around 0.20 was needed to reduce the temperature by around 1.00°C in April. In contrast, the green space proportion around 0.65 was required to decrease the temperature by around 1.00°C in February. Furthermore, in April, the differentiated temperature between the proportion of green space at 0.00 and 1.00 of the area was as high as 4.00°C. However, in February, the differentiated temperature between the proportion of green space at 0.00 and 1.00 of the area was as low as 1.50°C. The proportion of green space and the decreased temperature is presented in Figure 6.

Based on the LST extraction from the Landsat series, their thermal resolution images (100×100 m.) present the maximum and minimum ranges of LST over the diversity of LULC. Therefore, the green space proportion, such as grass and trees, could considerably cool surface temperature and provide regional cooling. This explored result corresponds with Armson *et al.* (2012) study.

Feasibility test of the selected green space proportion in hotspot mitigation

The feasibility test of the selected green space proportions used in hotspot mitigation was done with the 2014 and 2016 data. The results are shown in Table 9.

Table 9. Estimated results based on the selected green space proportion (°C)

c		31 March 2014		16 April 2014		20 March 2016		5 April 2016	
		Decreased Temperature (°C)	ΔT (°C)	Decreased Temperature (°C)	ΔT (°C)	Decreased Temperature (°C)	ΔT (°C)	Decreased Temperature (°C)	ΔT (°C)
1	Min	42.62	1.66	38.94	2.08	40.55	0.55	42.86	1.35
	Max	44.46	1.66	40.60	2.08	43.02	0.55	44.84	1.35
	Mean	43.80	1.66	39.35	2.08	41.59	0.55	43.87	1.35

Note: 1. The differentiated temperatures between the maximum temperatures in the hotspot and its surrounding areas in March 2014, April 2014, March 2016, and April 2016 were 0.43, 1.13, 0.76 and 0.25 °C, respectively.

2. ΔT is the differentiated temperature between the actual and decreased temperatures.

The selected green space proportion around 0.45 of the area was used in the hotspot to decrease the hotspot temperature to near or equal to the temperature of the surrounding area. At least decreased temperature is the differentiated temperatures between the maximum temperatures in the hotspot and its surrounding areas in March 2014, April 2014, March 2016, and April 2016 were 0.43, 1.13, 0.76, and 0.25°C, respectively. Based on the details shown in Table 9, the selected green space proportion could reduce the temperature data, except on 20 March 2016. On 20 March 2016, there was a minimal differentiation in temperature, and it had the most minor decrease (around 0.21°C).

Conclusions

As a result of this research, the SW is recommended for generating the LST over a small city, Buriram municipality, Thailand. The SW method can be employed with free download satellite data, such as the Landsat series. This method presents a more complex surface with finer LST data than other technics, the Radiative Transfer Equation-based method, the Improved Mono-Window method, and the Generalized Single-Channel method. According to the finer LST data, generating LST in small cities is essential. The finer LST is also required in generating hotspot identification in small cities. However, the accuracy of the calculated LST from the SW technic depends on the available data from the nearest local weather station.

Consequently, the generated surface temperature shows the clustering data from hotspot analysis that can present hotspots in several areas in Buriram municipality. Then, a regression model was employed to estimate the green space proportions associated with heat hotspot areas. As a result of this study, the proportion of green space show 30% to 60% for a potential hotspot reduction. The proportion of green space relies on the temperature of the hotspot and surrounding areas. With this research design and technic, the heat hotspot can be mitigated separately by considering the optimal proportion of green space related to the hotspot's size and temperature variation.

This technic is suitable for urban planners for monitoring the heat island, mitigating the heat hotspot, and planning to reduce the severe LST from the urban expansion. Routine work monitoring heat hotspots over the city area must be an essential mission for urban planners. Urban expansion is a typical phenomenon that can be planned regarding the optimal green space proportions in potential heat hotspot areas, particularly small cities. Urban planners may consider adding green space differently; however, they can generate the LST of the pre and post-solution by using the SW technic, elaborated in this study. This study promisingly shows a simplified technic that can calculate the green space proportion related to a hotspot area. With this benefit, it is flexible for urban planners to design the pattern and area of green space area differently according to the available space in a hotspot area. Typically, small cities lack the space for green space, leading to heat hotspot areas. Although the city center is limited with space for multi-activities, adding the shed trees along the street can be considered due to the limited public space in the hotspot area. However some available public areas, Park Cool Island (PCI) in several shapes can potentially promote LST mitigation. The technic of this study provides a tool to justify the size of green space acquired in a hotspot area and also a tool to monitor the adjusting proportions of green space associated with the hotspot temperature. The LST estimation and hotspot generation can be calculated regularly to monitor the UHI that affects the well-being of residents. The procedure and proposed method can apply to more than 30 small cities, with less than ten km², in Thailand, such as Phon Municipality (three km²) and Phatum Thani Municipality (seven km²).

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