Integrating Biophysical and Socioeconomic Data to Support Land Surface Temperature Analysis: An Example in Hong Kong

Wong, M. S.,[1] Shaker, A.,[2] and Lee, K. H.,[3]
[1]Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University Hung Hom, Kowloon, Hong Kong, E-mail: wongmansing.charles@gmail.com
[2]Department of Civil Engineering, Ryerson University, Canada, E-mail: ahmed.shaker@ryerson.ca
[3]Department of Satellite Geoinformatics Engineering, Kyungil University, Gyungsangbukdo, Korea E-mail: khlee@kiu.ac.kr

Abstract
The biophysical and socioeconomic factors are thought to have close relationships with the Land Surface Temperature (LST) due to the physical characteristics of green areas, building spaces and the influences of socially-related and economically-related factors. This study spatially and quantitatively examines the influences of biophysical and socioeconomic data on LST using Landsat TM image and census data in Hong Kong, and attempts to model the LST by a few but effective integration methodologies. The selected biophysical factors include Normalized Difference Vegetation Index (NDVI) and Normalized Difference Building Index (NDBI). The socioeconomic data includes population density, per capita income, percentage of college graduates, percentage of modern building, percentage of old buildings and village houses, and building density. Data integration using the Principal Components Analysis (PCA) and Stepwise Regression (SR) revealed that the NDVI and NDBI are the prominent factors on LST. The NDVI has an inverse relationship with the LST while the NDBI has a positive correlation. These support the facts that green areas provide a cooling effect to the surroundings in a city and the increase in building spaces leads to a rise in LST. It is also noted that high-income, highly educated families prefer to live in green and open space areas, and old buildings and antique villages in Hong Kong still preserve green areas. The backward SR method shows the strongest correlation (r=0.836 and s.d.=0.586) exists between LST and the biophysical/socioeconomic parameters. These findings can be used for investigating other urban thermal environments and as measures for analyzing the mitigating effects of urban heat island caused by socio-related factors.

1. Introduction

Hong Kong, a tropical climate city, has suffered from the urban heat island effect caused by the high-rise buildings and high density urban areas for years. The Hong Kong urban population shows a greater sensitivity to heat island effect than the countryside. The temperature differences between rural areas and city downtown areas have a range of 1.5 to 4°C in summer daytime and 2 to 6.5°C in winter daytime while it is expected to be more significant in night-time and early morning (Fung et al., 2009). Many socioeconomic data have been reported to have relationships with heat waves, e.g. age, gender, hospital inpatients, deprivation (London UHI, 2006), but only a few studies have examined the relationships between Land Surface Temperature (LST) and biophysical/socioeconomic data. LST can be retrieved from space by covering the whole cities and regions from remote sensing platforms.

Many research have been done to retrieve accurate LST for years, these include airborne multispectral scanners (Asrar et al., 1988 and Holbo and Luvall, 1989), the NOAA AVHRR satellite series (Platt and Prata, 1993, Johnson et al., 1993 and Prata, 1994), MODIS (Wan, 1999 and Jacob et al., 2004), Landsat TM (Honjo and Takakura, 1987), TERRA ASTER (Yamaguchi et al., 1998) and SEVIRI/METEOSAT (Peres and DaCamara, 2005 and Trigo et al., 2008). The majority of these researches dealt with retrieving LST but few of them focused on analyzing the patterns and relationships existing between LST and biophysical/socioeconomic data. Biophysical data refers to the vegetation cover and the structural characteristics of the vegetation. Yue and Tan (2007) using nine land cover types in their study of Shanghai, noted the Normalized Difference Vegetation Index (NDVI) was inversely correlated with LST.

Ouyang et al., (2007) demonstrated that the NDVI was a prominent indicator for correlating with LST measurements. Apart from studies examining the relationship between LST and biophysical data, only a few have examined the relationship between LST and socioeconomic data, which refers to the population and economically-related data, such as population density, per capita income, and percentage of college graduates. Chen and Zhou (2004) examined the relationships between the fraction of urban surfaces, population density and LST. They found a strong correlation between the fraction of urban surfaces and LST, and a moderate correlation between population density and LST. This is not surprising since urbanization increases the solar absorption on wall surfaces and rooftops, and decreases the water availability for evapo-transpiration thus leading to raise the LST. Xiao et al., (2005) showed similar findings where a moderate correlation was seen between LST and population density, but the built-up ratio had a stronger correlation with LST. Thus, it can be observed that using a single parameter may not work well for correlating different variables on LST. Since Lo and Faber (1997) and Li and Weng (2007) examined several socioeconomic parameters for modeling the Quality of Life (QOL), different data integration techniques have been investigated including the Principal Component Analysis (PCA), factor analysis and GIS overlay ranking method. Additionally, in the studies of Beijing (Xiao et al., 2005 and Ouyang et al., 2007), stepwise regression (SR) models were also actualized for studying the relationships between LST and biophysical/socioeconomic data. In this study, the relationships between biophysical/socioeconomic data and LST were examined using (i.) individual parameters, and (ii.) integrated parameters. Different integration methods were applied to correlate and retrieve LST based on different parameters.

2. Study area and Data used

The present study was carried out in the north-west districts of Hong Kong, comprising several "satellite towns" with different degrees of urbanization. The concept of "satellite towns" was first used by the Hong Kong Government in the 1970s in its plan to modernize dormitory towns. Towns with different degrees of urbanization are found in the north-west districts, these include the densely urbanized Tuen Mun which is located in a coastal valley, the newly developed Tin Siu Wai which has a high population density, and Yuen Long, an old district with antique villages and a high population density (Figure 1).

Three primary data sources were used in the study:

(i.)Landsat TM daytime image acquired on the 28th December 2006 at around 10:30 a.m. local time (this is the only available cloud-free image on the year).

(ii.)The census data of year 2006 for the Tertiary Planning Units (TPU) issued by the Census and Statistics Department in Hong Kong. The census data covers different socioeconomic parameters such as population density, per capita income, percentage of college graduates, percentage of modern building, percentage of old buildings and village houses, and building density (Census and Statistics Department, 2006).

(iii.)The GIS polygons of TPU from the Planning Department of Hong Kong.

3.1 Orthorectification

The Rational Function Model (RFM) (Tao and Hu, 2001) was adopted for image orthorectification of the Landsat image with twenty five well identified Ground Control Points (GCPs) distributed on the study area and a high resolution 10m Digital Elevation Model (DEM). The GCPs were selected from the high contrast features on the 1:5000 GIS road and building layers, and the DEM was created from the 1:5000 GIS contour layers. The Root Mean Square Error (RMSE) for the GCPs is approximately half a pixel for both East-West and North-South directions. The orthorectified Landsat image was also validated with existing digital orthophoto for assessing its spatial accuracy and RMSE, and a 0.6 pixel accuracy was achieved.

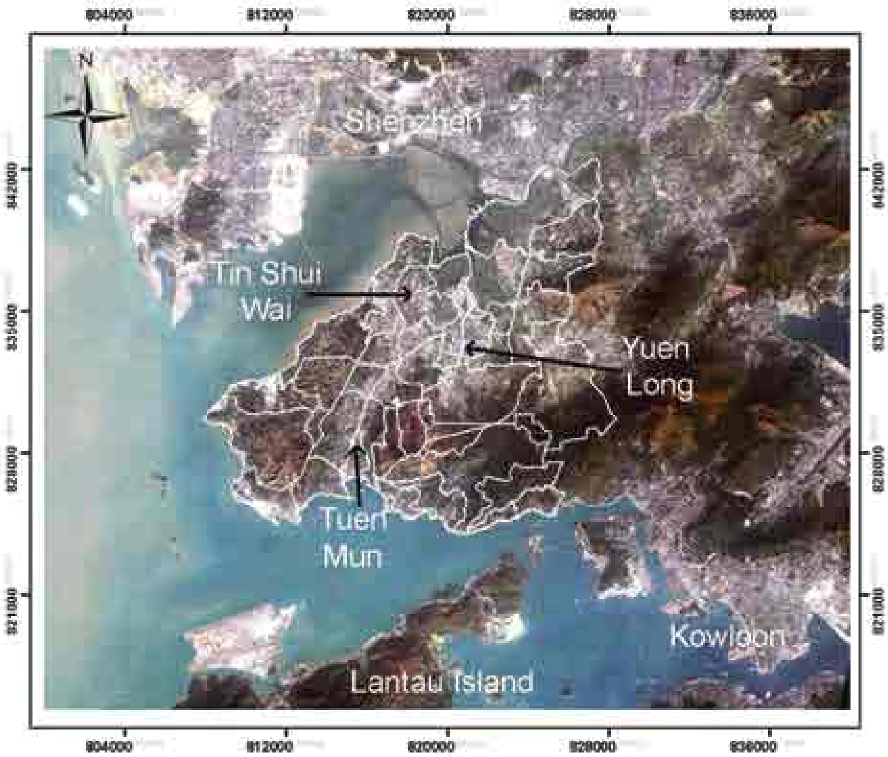
3.2 Radiance to Emissivity Corrected Land Surface Temperature

The spectral radiance image was first converted to the brightness temperature (BT) image. The surface emissivity maps were then produced from six broad land covers map, namely forest, water, grassland, shrubland, urban, and soil/sand. The correction of the emissivities from different land covers were suggested using equation 1 (Artis and Carnahan, 1982) with different emissivity values (Nichol, 1994, 1996).

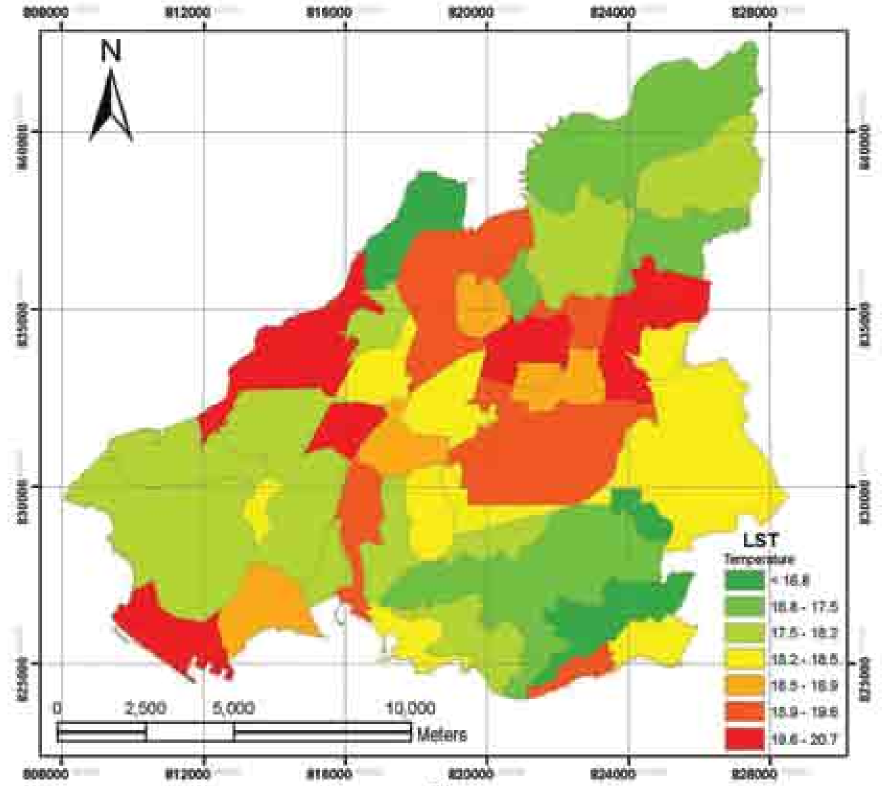
$$T_s = \frac{T_b}{\varepsilon^{\frac{1}{4}}}$$

Equation 1

where T_s is the LST, T_b is the BT, ε is the emissivity value.



a)



b)

Figure 1: a) Location of study area, overlaid with TPU polygons and Landsat image, b) LST map derived from Landsat image

4. Methodology

Remote sensing derived biophysical variables were considered in this study, including NDVI and NDBI. NDVI measures the degree of abundance of vegetation covers and NDBI measures the degree of abundance of building spaces (Zha et al., 2003). The algorithms for deriving NDVI and NDBI are expressed in equation 2 and 3.

$$NDVI = \frac{NIR\text{-}Red}{NIR\text{+}Red}$$

Equation 2

$$NDBI = \frac{SWIR\text{-}NIR}{SWIR\text{+}NIR}$$

Equation 3

The selected parameters in the socioeconomic database are (i.) population density (PD), (ii.) per capita income (PCI), (iii.) percentage of college graduates (PCG), (iv.) percentage of modern building (PMB), (v.) percentage of old buildings and village houses (POV) and (vi.) building density (BD). These parameters were suggested by Lo & Faber (1997) in their study of quality of life. Comparing the effect of each variable with LST was accomplished using the correlation coefficient. First, regression model was assessed for each variable with LST. Second, the biophysical and socioeconomic data were integrated using (i.) Principal Components Analysis (PCA) with regression, and (ii.) Stepwise Regression (SR) analysis. The highest correlation coefficient obtained from these models suggests the best-fit integration method for building the relationship with LST.

4.1 Study of Individual Parameters

Pearson's correlation was adopted for calculating the relationships of the eight parameters. Table 1 shows the correlation matrix of the eight parameters. The NDVI is a competent variable as a good indicator of environmental quality analysis (Lo and Faber, 1997). Strong negative correlations were shown between LST and NDVI ($r=-0.687$ at 0.01 level of confidence), and between NDBI and NDVI ($r=-0.716$ at 0.01 level of confidence). LST definitely has a negative correlation with NDVI since greening is the medium for cooling the surface through evapotranspiration. The strong correlation between NDBI and NDVI is also expected as the increase in abundance of building space decreases the vegetation space. Moreover, the NDBI has a strong positive correlation with LST since increase in building spaces always increases surface temperature ($r=0.749$ at 0.01 level of confidence). From the correlation table (Table 1), we also observe the percentage of old buildings and village houses have a moderate negative correlation with the percentage of modern buildings. This is a fact of urban modernization i.e. new buildings replacing antique villages. The building density shows a moderate negative correlation with the percentage of old buildings and village houses, which means the new buildings are predominant on the building density in TPU polygons. Due to the correlations existing among these eight variables with different degrees of significance, it is essential to integrate them in order to enhance the correlation and model the LST. Several integration methods including PCA and SR will be discussed in the following sections.

Table 1: Correlation matrix of eight biophysical and socioeconomic parameters

	PD	**PCI**	**PCG**	**PMB**	**POV**	**BD**	**NDVI**	**NDBI**
PCI	-0.210							
PCG	-0.113	0.188						
PMB	0.021	0.086	0.007					
POV	-0.035	-0.218	-0.120	-0.497**				
BD	0.022	-0.032	-0.032	-0.047	-0.415**			
NDVI	-0.138	0.049	0.036	0.016	0.110	-0.184		
NDBI	0.091	-0.132	0.025	0.073	-0.195	0.109	-0.716**	
LST	0.127	-0.247	-0.073	0.232	-0.280	0.116	-0.687**	0.749**

** Correlation is significant at the 0.01 level (2-tailed).

PD - population density
PCI - per capita income
PCG - percentage of college graduates
PMB - percentage of modern building
POV - percentage of old buildings and village house
BD - building density
NDVI – Normalized difference vegetation index
NDBI – Normalized difference building index
LST – Land surface temperature

4.2 Study of Integrated Parameters

4.2.1 Principal components analysis (PCA)

Principal eomponents analysis is a data compression teehnique often used in remote sensing. The rationale of PCA is to reduee the amount of noise in data and attempt to retain the accuracy and effectiveness. PCA is a scene-dependent algorithm which generates weight factors through a linear transformation. Normally, most of the useful data is loaded in first few PCs (eg. PC1, PC2 and PC3), while the noise can be found in the last few PCs. The PCA was carried out using software SPSS 13.0 in this study. Table 2 listed the percentage of variance of each PC. While the first four PCs dominated 72.6% of the total variance of the LST, the factor analysis was then applied based on the PC 1-4 using the following expression (Equation 4):

$$PC_i = \sum A_i V$$

Equation 4

where i=1-4, PC is the principal component, A is the coefficient of the variable, V is the eight socioeconomic and biophysical variables.

Table 2: The percentages of variances and principal components loading matrix

PC	% of Variance
1	24.751
2	20.275
3	14.739
4	12.866
5	10.905
6	9.517
7	4.047
8	2.900

Table 3: Coefficients of principal components

	1	2	3	4
PD	0.225	-0.354	-0.508	0.194
PCI	-0.035	0.622	0.388	0.013
PCG	0.022	0.381	0.553	0.098
PMB	0.339	0.542	-0.404	0.529
POV	-0.621	-0.628	0.252	0.085
BD	0.483	0.142	-0.178	-0.805
NDVI	-0.761	0.386	-0.331	-0.075
NDBI	0.784	-0.327	0.311	0.204

Table 3 illustrates the loading of variables of the first four components. Comrey and Lee (1992) and Li and Weng (2007) stated the loading ranges for interpreting component weights, they suggested the loadings above 0.71 is high; 0.63 is very good; 0.55 is good; 0.45 is fair and 0.32 is poor. The detailed spatial distributions of PC 1-4 are displayed in Figure 2 (a, b, c, d). The PC1 is highly influenced by the percentage of old buildings and village houses (NDBI and NDVI). The spatial distribution of PC1 is indicated by the dominance of greenness within the study area. The PC2 is characterized by the percentage of old buildings, village houses and per capita income. The population density and the percentage of college graduates are the prominent factors in PC3, while the percentage of modern buildings and building density are prominent in PC4. Since the four PCs have exclusive characteristics based on different combinations of variables, integration and regression of these variables will be expeeted to have meaningful results and higher correlations with LST. Equation 5 shows the expression of multiple regression of PC1-4 correlated with LST. To investigate the agreement of this model, correlation coefficient was performed. A high correlation was obtained between the combination of PC1-4 and LST where r=0.710 at 0.01 level of confidence. The modeled LST was then obtained by adding the coefficients of each variable and expressed in equation 6. Figure 3 shows the modeled LST from PCA analysis.

$$LST=19.745+3.815*PC1-1.762*PC2+1.951*PC3+1.704*PC4$$

Equation 5

$$LST = 0.822*PD-0.450*PCI+0.659*PCG+0.451*PMB-0.626*POV-0.127*BD-.357*NDVI+4.522*NDBI+19.745$$

Equation 6

Among all the parameters used in equation 6, the population density, percentage of college graduates, percentage of modern building and NDBI tend to have positive correlations with LST. On the contrary, the per capita income, the percentage of old buildings and village houses, the building density, and the NDVI tend to have negative correlations with LST. A surprising finding is the negative correlation between building density and LST, where increase in building density decreased LST. In this study, the building density is defined as: the number of buildings/area. All 46 TPU polygons have a very limited range of building density from values of 0.00001 to 0.029. This limited range of building density may not be good enough to model LST.

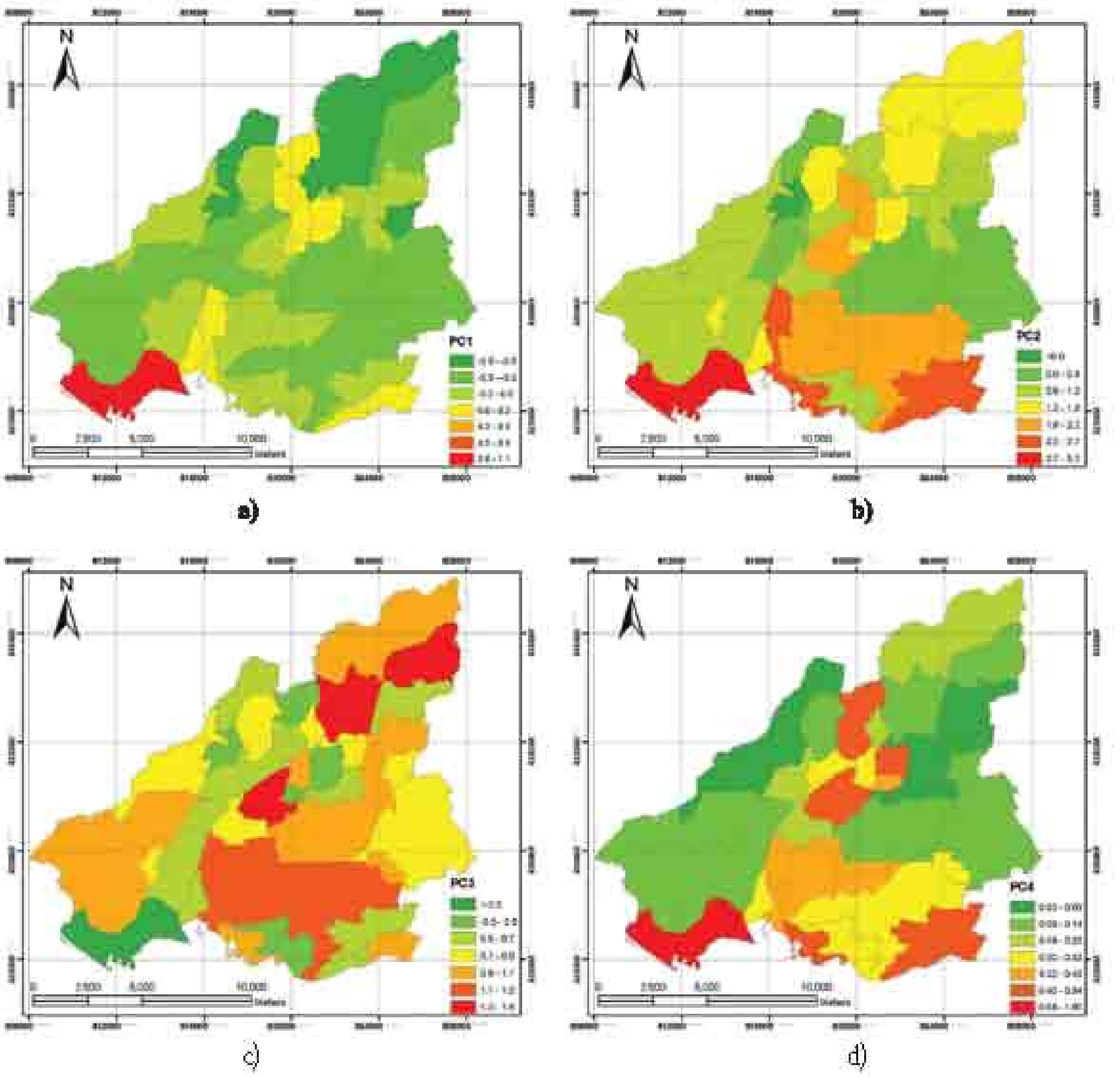


Figure 2: The principal components maps, a. PC1, b. PC2, c. PC3, d. PC4

4.2.2 Stepwise regression

Stepwise regression is a regression model allowing the interaction by user in selecting the appropriate variables using the method of (i.) forward selection, which adds extra variables to those which are statistically significant, and (ii.) backward selection, which eliminates the variables in those which are not statistically significant. Both forward and backward selection stepwise regressions were executed in software SPSS 13.0. Xiao et al., (2005) and Ouyang et al., (2007) used SR models for studying the relationship between LST and biophysical data in Beijing. They were able to achieve high correlations by integrating parameters for deriving the LST but restricted by the limited numbers of socioeconomic data. In this study, the forward selection stepwise regression was first performed. The variables were added if they are statistically significance ($p<0.05$).

Next, the backward selection stepwise regression was executed where the variables were removed if they are not statistically significance ($p>0.1$). It is noted that the combination of NDBI, NDVI, PMB, and PCI has the strongest correlation with LST ($r=0.826$) in the forward SR models (Table 4). But, the LST correlated stronger with the combination of NDBI, PCG, PMB, BD, PCI, POV, NDVI ($r=0.836$) and obtained the smallest standard error (s.d.=0.586) among all five models in backward stepwise models. The equation of this model is expressed in equation 7 and the modeled LST is displayed in Figure 4.

$$LST=19.790-0.308*PCI-0.245*PCG+0.188*PMB-0.586*POV-11.482*BD-5.946*NDVI+6.631*NDBI$$

Equation 7

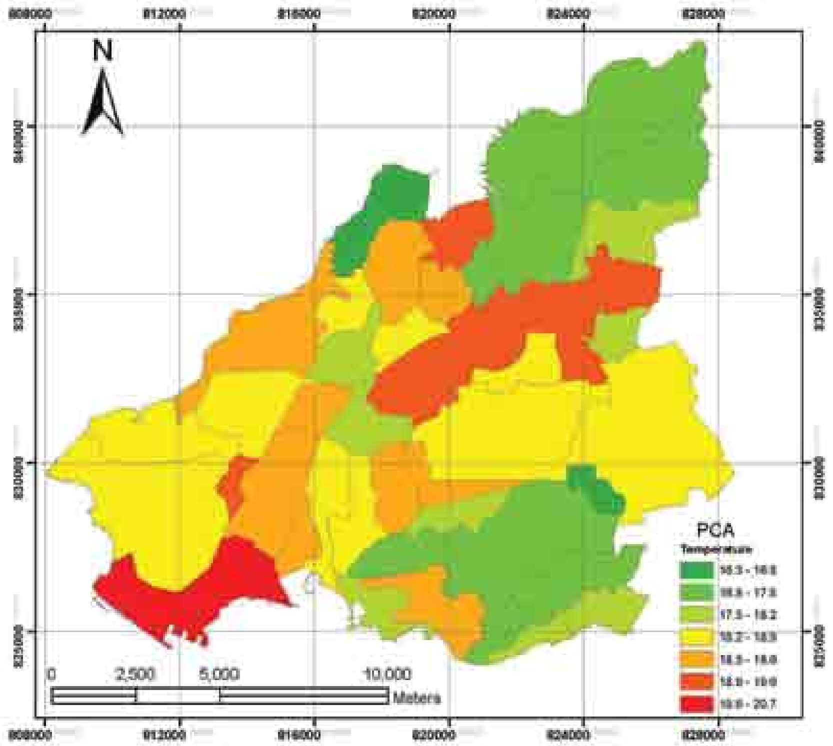


Figure 3: Modeled LST map, derived from PCA

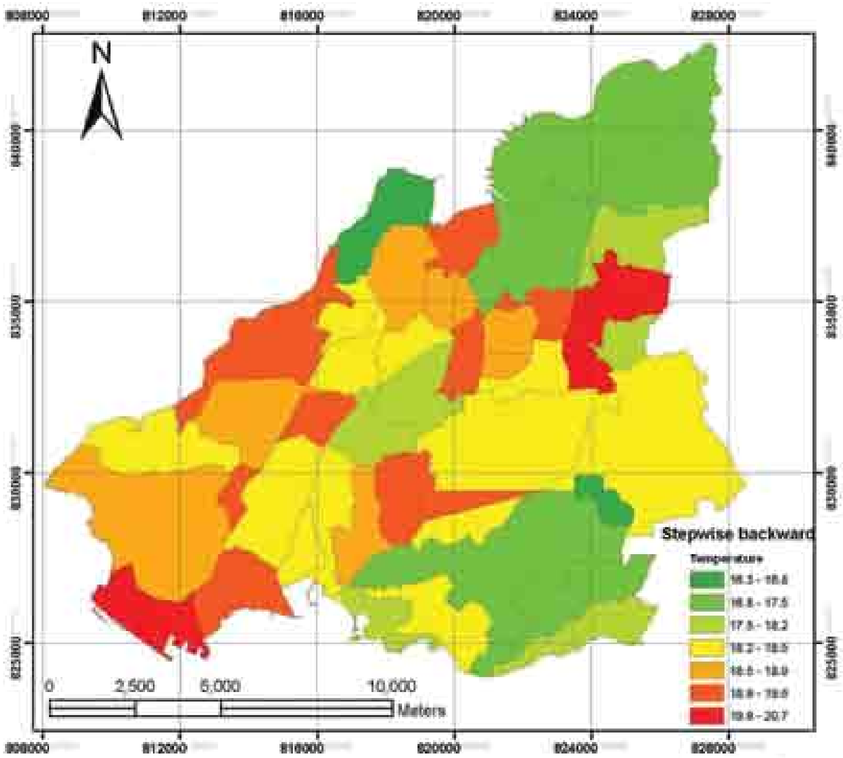


Figure 4: Modeled LST map, derived from stepwise backward regression model

Table 4: Correlation coefficients and standard errors of forward stepwise regression with LST

Model	R	Std. Error of the Estimate
NDBI	0.749	0.657
NDBI, NDVI	0.780	0.628
NDBI, NDVI, PMB	0.805	0.602
NDBI, NDVI, PMB, PCI	0.826	0.579

Table 5: Correlation coefficients and standard errors of backward stepwise regression with LST

Model	R	Std. Error of the Estimate
NDBI, PCG, PMB, BD, PD, PCI, POV, NDVI	0.836	0.594
NDBI, PCG, PMB, BD, PCI, POV, NDVI	0.836	0.586
NDBI, PMB, BD, PD, PCI, POV, NDVI	0.834	0.581
NDBI, PMB, PCI, POV, NDVI	0.832	0.577
NDBI, PMB, PCI, NDVI	0.826	0.579

Similar finding was observed from the PCA model, however the population density does not show any statistical relationship with LST in equation 7, and the percentage of college graduates correlated negatively with LST. Based on equations 6 and 7 from the PCA and stepwise models, it can conclude that the NDVI and NDBI played prominent roles on LST.

5. Discussion and Conclusions

This study demonstrates the relationships between LST and human activities presented by biophysical and socioeconomic data. The study also modeled LST through integration techniques (PCA and SR) based on socioeconomic and biophysical data. The study area was situated in the north-west districts of Hong Kong comprising several towns having different degrees of urbanization. This helped in investigating a broader range of socioeconomic data e.g. from new towns to rural areas, and their influences on LST. From modeling the relationships between LST and individual biophysical and socioeconomic factors, it was discovered that population density does not correlate well with LST, where NDVI and NDBI are predominant variables in the model. Similar low correlation between population density and LST was also observed in Chen and Zhou (2004) (r=0.47). Although Oke (1973) found that LST increases as the logarithm of the population, e.g. a population of 10 has an urban warming of 0.73 °C, and a million people population has a warming of 4.4 °C, this relationship may not be significant in a single year of census data and remote sensing data which is derived from a single image time although it is closely related to the urban structure and activities. Positive correlations were shown to exist between LST and percentage of modern building, and NDBI, while negative correlations were found between per capita income, percentage of college graduates, percentage of old buildings and village houses, and NDVI. These findings are consistent with the perceptions of Hong Kong environment where modern planning designs which do not take green areas into consideration, result in temperatures increasing with increases in building spaces. This phenomenon is evident in the positive correlation between PMB and NDBI. Similar findings observed from Zhang et al., (2009), they utilized both NDVI and NDBI as surrogates of landcover to investigate the relationship of LST and to quantify the degree of urbanization in Fuzhou, China. Since NDBI shows the percentage of built-up areas, higher NDBI value, denser built-up areas, thus increased LST will be observed from more anthropogenic heat discharge and poor ventilation in the densely built up areas. Secondly, high-income and highly-educated families prefer to live in green areas and more spaces. This fact is evident in the negative correlation between LST and PCI, PCG respectively. Thirdly, old buildings and antique villages still preserve green areas (e.g. front and back yards), therefore increasing the percentage of old buildings can decrease LST. Finally, Nichol and Wong (2008) showed green patches with a minimum area of 450m^2 can provide a cooling effect on the surroundings, and thus NDVI is found to be negatively correlated with LST in this study. On the basis of statistical analysis, the lowest correlation was obtained from the PCA regression model (r=0.710) using all eight parameters. The backward SR model gave the strongest correlation with LST. A high correlation coefficient (r=0.836) and minimum standard deviation (s.d.=0.586) were achieved from the combinations of NDBI, PCG, PMB, BD, PCI, POV, NDVI. Although Weng et al., (2006) and Ouyang et al., (2007) yielded slightly higher multiple coefficients (r=0.927, r=0.935) using multiple regression with LST in Indianapolis, U.S. and Beijing, China respectively, more parameters used and larger spatial coverage in their studies may explain these small advantages. The urban thermal environment is complex and can vary with other factors not be considered, however, these findings from this study can be implemented in urban planning since they are practical enough for analyzing urban heat island mitigation. Further analysis will be carried out by investigating different factors and different integration methodologies.

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