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Assessing urban growth dynamics of major Southeast Asian cities using Night-Time Light data

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This study analysed urban growth patterns for 15 Southeast Asian cities using remotely sensed night-time light data from 1992 to 2012. We extracted three urban categories (countryside, peri-urban, and core-urban) for each city using objectively derived thresholds from the Brightness Gradient (BG) approach. The peri-urban and core-urban combined categories were generally found to increase over time for all cities whereas countryside urban category decreased implying strong spatial and temporal trends in urbanization. These trends were also found to be sensitive to geographic characteristics of cities. The study showed that the BG approach can be successfully applied to extract and study growth dynamics of different urban categories for Southeast Asian cities having range of demographic and socio-economic conditions. The BG derived urban categories compared favourably with Landsat derived impervious areas, where the former was found to envelope the high percent impervious region derived from the latter. The BG derived urban areas are lastly compared against the population data to explore linkages with population growth.

Keywords: urbanization dynamics; night-time light; Landsat; brightness gradient; Southeast Asia

1. Introduction

It is well-recognized that the effect of urbanization on the environment is manifold, including the loss of agricultural land, urban heat island effect and associated increase in near-surface temperature, increases in carbon emissions and air pollution, and the depletion of natural resources (Seto, Sánchez-Rodríguez, and Fragkias 2010; Schneider, Friedl, and Potere 2010). The rapid rate of urbanization also poses numerous challenges including infrastructure design, water resource management, and public health. The last century has witnessed an increasing concentration of people in urban regions. For example, the worldwide urban population in the last 25 years has grown by 73% compared 38% for total population (UNESCAP 2014). Similarly, the urban population percentage increased from 43% in 1990 to 54% in 2015, and is expected to reach 66% by 2050 (UNPD 2014). These urbanization rates depend on various factors such as the geography, socio-economic conditions, and the political environment. For instance, the urban population percentage in developed and high-income countries is projected to increase at a lower rate compared to less developed and low-income countries.

Currently, the world's fastest growing cities are concentrated in the Global South, (i.e. Africa, Latin America) and in developing Asia (UNPD 2014). In particular, Asia and Southeast Asia (SEA) are home to sprawling megacities such as Tokyo, Bangkok, Jakarta, and Manila, with population exceeding 10 million. SEA region is steadily urbanizing with about 245 million people (42% of total population) living in urban areas and it is predicted that the urban population will increase to 47% percent by 2025 (Aritenang 2014). Further the SEA region possesses a wide range of urbanization levels ranging from economically advanced countries (e.g. Singapore and Malaysia) to less developed countries (e.g. Cambodia and Myanmar). SEA cities also have large geographic variability compared to those in US, China, and India because of the complex

land-sea structure of the SEA region. Understanding and modelling the spatio-temporal dynamics of urbanization of these cities as conditioned on multiple factors (e.g., economic, geographic, and political) is essential for developing appropriate planning and management strategies.

Socio-economic and census data are good data sources in urbanization studies (Henderson et al. 2003; Chen et al. 2014). However in many less-developed and developing nations, such data is frequently unavailable at desired spatial and temporal resolutions for modelling urban growth dynamics (e.g. Masek, Lindsay, and Goward 2000). In such situations, remote sensing can be a dependable alternative, providing data at multiple spatial and temporal scales. Satellite data is more suited to extract urban areas because of the satellites' high visit rates and the availability of archived datasets over a long period. Satellite-based observations with various spatio-temporal resolutions have been applied to investigate urban growth patterns and urbanization impacts on natural systems (Masek, Lindsay, and Goward 2000; Seto et al. 2011; Ma et al. 2012; Ma et al. 2015). Optical data, and especially the Landsat data has been extensively used in many studies to analyse urban growth patterns, and urban land-use and land-cover changes (Masek, Lindsay, and Goward 2000; Seto et al. 2002; Bhatta 2010) and shown to be useful in planning for sustainable urban growth (Seto et al. 2002). Spatial patterns of land cover changes for metropolitan cities have also been assessed using fine and medium resolution remotely sensed data, e.g. the Moderate Resolution Imaging Spectroradiometer (MODIS) with a resolution of 500 m that can be used to produce maps of urban regions at a global scale (Schneider, Friedl, and Potere 2009; 2010).

Another source of remote sensing data is the Defense Meteorological Satellite Program (DMSP) OLS Night-Time Light (NTL) data. The NTL data has been widely used to monitor urbanization at regional and global scales (e.g. Henderson et al. 2003;

Small, Pozzi, and Elvidge 2005; Liu et al. 2012; Ma et al. 2012; Zhang and Seto 2013; Elvidge et al. 2014; Ma et al. 2015). The major advantage of using NTL data is that it captures information related to anthropogenic activity. Thus urban growth patterns extracted from NTL data analysis are shown to be strongly correlated with social and economic variables such as population, GDP and electric power consumption (Sutton et al. 2001; Doll, Muller, and Morley 2006; Chand et al. 2009), making it a good proxy to model urbanization.

Extracting and mapping urban extent from NTL raw imagery is a key task. Hence, researchers developed various techniques such as thresholding (Imhoff et al. 1997; Elvidge et al. 2009; Henderson et al. 2003) and also image classification method (Cao et al. 2009) to generate urban extent maps from NTL imagery at different spatial scales. Of these methods, thresholding approach has been widely used to extract urban information from NTL data. However, a major issue of underestimation or overestimation arises when using a single threshold, and as such, no single brightness threshold is universally applicable for mapping urban boundaries from NTL imagery (Small, Pozzi, and Elvidge 2005; Small et al. 2011). An alternative cluster based approach was developed by Zhou et al. (2014) to reduce the constraints from general thresholding approaches. In this approach, an optimal threshold for each cluster is estimated using the cluster size and the overall night-light magnitude in each cluster. A global urban map was then generated using this cluster based method. However, such single optimal threshold techniques also have drawbacks; they fail to capture different degrees of anthropogenic activity at a local scales (e.g., within a city). In order to overcome this constraint, Ma et al. (2015) proposed an approach to better reflect the spatio-temporal dynamics of urban process from NTL brightness at a local scale. This approach partitions the NTL imagery into different urban

categories which are then linked with anthropogenic activity and urbanization level at local scales.

Most studies related to the dynamics of urbanization are for the regions of US, Europe, China, and India with very few studies for SEA (e.g. Herold, Goldstein, and Clarke 2003; Batty 2007; Luo and Wei 2009; Chand et al. 2009; Seto et al. 2011). Schneider et al. (2015) characterized urban transitions in more than 1000 cities in East Asia and SEA by analysing MODIS data for years 2000 and 2010. Small and Elvidge (2013) studied the decadal changes in anthropogenic night light in Asia, focusing on India and China and indicated that growth trajectory in SEA was different to that of India and China. A comprehensive spatio-temporal characterization of urban growth across Southeast Asian cities is still lacking.

The main objective of this work is to analyse the dynamics of urban growth in 15 major SEA cities using NTL data from 1992 to 2012. We evaluated three recently developed inter-sensor calibration approaches (Wu et al. 2013; Elvidge et al. 2014; Zhang, Pandey, and Seto 2016) for the SEA region as the raw NTL data varies significantly with sensor and over time. Specifically for each city, we categorized NTL data for each year as countryside (CS), peri-urban (PU) and core-urban (CU) categories, and quantified the spatio-temporal trends for each category. The thresholds employed were obtained using a recently proposed Brightness Gradient (BG) approach (Ma et al. 2015). Section 2 provides a description of the data, the cities chosen, the BG approach, and the three calibration techniques. The results are presented in section 3 followed by concluding remarks in section 4.

2. Data and Methods

2.1 Data

This study uses stable lights NTL annual composite dataset version 4 for the years 1992 to 2012 as downloaded from the National Centers for Environmental Information (NCEI) website (<http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>). This stable lights dataset captures persistent lights from global cities and sub-urban areas under cloud free conditions. These data products have 30 arc-sec spatial resolution (~1 km near the equator), global coverage ranging between -180° to 180° longitude and -65° to 75° latitude, with 6-bit radiometric resolution (i.e. 64 levels). These datasets for the years 1992-2012 have been acquired by six different satellite missions namely DMSP F10, F12, F14, F15, F16 and F18.

The study also used data from Landsat – Thematic Mapper (Landsat 5 TM), containing seven spectral bands (six visible and one thermal). The spatial resolution is 30 m for visible bands and 120 m for the thermal band. This dataset is downloaded from the U.S. Geological Survey (USGS) earth explorer website (<http://earthexplorer.usgs.gov/>).

2.2 NTL data processing

It is well-known that the non-availability of on-board sensor calibration limits the usage of the raw NTL data for urban growth studies (Elvidge et al. 2009; Zhang and Seto 2011; Elvidge et al. 2014). Sensor degradation, difference in sensor orbits and average annual composites can give different magnitude of lit pixels on the ground even when there is no change detected (Zhang and Seto 2011). Furthermore inter-sensor differences needs to be minimised through inter-sensor calibration (Wu et al. 2013; Elvidge et al. 2009; Elvidge et al. 2014; Zhang and Seto 2013). Bridging the inter-sensor gap in NTL data has

received more attention in the last few years with the increasing use of NTL for temporal analysis (e.g. characterizing trends). Three calibration methods have been proposed since 2009 to ensure continuity in NTL data across sensors (Elvidge et al. 2009; Wu et al. 2013; Zhang, Pandey, and Seto 2016). Although, assessment of these approaches has been conducted at global scales, their merits and disadvantages at a regional scale is not fully understood.

The technique proposed by Elvidge et al. (2009) involves the selection of a reference area that has undergone least changes in NTL patterns over time, and fitting a second-order polynomial as follows:

$$D_{\text{cal}} = C_0 \times D_{\text{raw}}^2 + C_1 \times D_{\text{raw}} + C_2 \quad (1)$$

where

D_{cal} denotes calibrated NTL digital number (DN) data;

D_{raw} denotes raw NTL digital number (DN) data; and

C_0 , C_1 and C_2 are coefficients of fitted quadratic equation;

This calibration approach has been shown to reduce the discrepancies between raw DN values captured by two different sensors in a single year. We used coefficient values from Elvidge et al. (2014) for years 1992 to 2012 here.

Zhang, Pandey, and Seto (2016) proposed a calibration approach which also involves fitting a second-order polynomial, but with coefficients estimated using a technique called ridge line sampling (RSL). The corresponding coefficients for this study were taken from Zhang, Pandey, and Seto (2016).

Wu et al. (2013) proposed an alternative strategy for inter-sensor calibration, which performs radiometric calibration as well as reducing errors caused by pixel saturation and inter-annual variation. This approach uses the following power function to calibrate raw DN values.

$$D_{\text{cal}} = a_1 (D_{\text{raw}} + 1)^{b_1} - 1 \quad (2)$$

where

D_{cal} denotes calibrated NTL digital number (DN) data;

D_{raw} denotes raw NTL digital number (DN) data; and

a_1 and b_1 are the coefficients of the fitted power law;

In this study, the coefficients a_1 and b_1 for each year from 1992 to 2010 were taken from Wu et al. (2013).

We first extracted the NTL data for the entire SEA region (Figure 1) and applied the three calibration approaches discussed above. It is noted that in Wu et al. (2013)'s approach, calibration coefficients were available over 1992-2010, while coefficients were available over 1992-2012 for other the two approaches. We analysed their sensitivity using the Sum of Normalized Difference Index (SNDI) developed by Zhang, Pandey, and Seto (2016) and selected the calibration approach that performs best for the SEA region. The calibrated NTL data is then extracted for 15 major SEA cities based on a bounding box for each city as shown in Figure 1. These 15 cities have been selected based on the criteria that population size exceeds one million according to 2015 year values (UNPD 2014). The bounding box coordinates and the population for each city are listed in Table 1.

For years having annual composites collected by two different satellite sensors, we have selected the latest sensor data in order to reduce the effect of sensor degradation. For compactness, the results from the three calibration approaches will be referred to as WU2013, EL2014, and ZH2016.

2.3 Extraction of urban categories from calibrated NTL data

Capturing the pixel level fluctuations is key in detecting spatial changes in the NTL data.

We employed the BG approach, proposed recently by Ma et al. (2015). The BG refers

to the spatial gradient in NTL over a pixel w.r.t. its neighbours. By considering spatial gradient instead of absolute NTL value, one can delineate urban areas according to different degrees of urbanization. For example, a flatter spatial gradient implies minimal NTL changes in space, which is expected either within core-urban regions or in relatively countryside/rural regions. Conversely, steeper spatial gradient implies a transition zone between core urban and countryside, i.e. peri-urban areas.

There are multiple ways in which the spatial gradient can be computed. Here we follow Ma et al. (2015)'s approach and used the maximum gradient technique of Burrough, McDonnell, and Lloyd (2015). The relationship between pixel-level DN and corresponding BG is modelled using the quadratic polynomial.

$$B = a_0 \times D_{\text{cal}}^2 + a_1 \times D_{\text{cal}} + a_2 \quad (3)$$

where

B denotes brightness gradient value;

D_{cal} denotes calibrated NTL digital number (DN) data; and

a_0 , a_1 and a_2 are the coefficients of the fitted polynomial;

The fitted polynomial is a downward parabola, which is used later to derive urban categories. While Ma et al. (2015) used five urban categories (low, medium-low, medium, medium-high and high), we have chosen three categories as some cities in our study are relatively smaller. The DN thresholds for extracting above three categories were calculated using the fitted polynomial (equation 3). First, the brightness gradient value B_1 was calculated as $(B_0 + 2B_{\text{max}})/3$, where B_0 and B_{max} are the lowest and highest BG of the rising limb of equation 3, respectively. Similarly, B_2 was calculated as $(B_{\text{max}} + 2B_3)/3$, where B_3 is the lowest BG of the falling limb of equation 3. The DN values corresponding to B_1 and B_2 were chosen as DN thresholds D_1 and D_2 to extract three urban categories. Specifically, all pixels with DN values ranging from 3 to D_1 were categorized as

countryside (CS), pixels with $D_1 < DN < D_2$ as peri-urban (PU), and pixels with $DN > D_2$ as core-urban (CU). The CU category pixels should represent the highly developed urban core with intense anthropogenic activity along with a high percentage of impervious area or built-up land. The PU category is attributed to the periphery of the core urban area with reasonable urban activity. The CS category includes areas with lower human activity such as agricultural sites and small villages. This approach involving DN thresholds which are city-specific avoids setting an arbitrary threshold for heavily urbanized areas that has large DN values. Lastly a minimum threshold of 3 is used because of high interannual variability of very low DN values. In this work, we applied the BG approach on the calibrated NTL data for all 15 cities.

2.4 Comparison of NTL urban extent with Landsat TM derived impervious area

The three urban categories extracted from BG approach are compared with the impervious area derived from Landsat TM data. The supervised maximum likelihood classification technique is applied on the Landsat TM datasets using ArcMap 10 software to extract the impervious areas or artificial surfaces. Training samples for the supervised classification were selected based on visual inspection (e.g., comparing with Google Earth imagery).

3. Results and discussion

3.1 Evaluation of inter-sensor calibration results

The Total Light Index (TLI) is the sum of all grey values in an NTL image, and is widely used to display and analyse interannual variability and volatility in NTL time series (e.g. Wu et al. 2013). The TLI results in a single value for a specific year for both uncalibrated and calibrated NTL datasets. The TLI values are then used to compute the SNDI (Zhang,

Pandey, and Seto (2016)) to evaluate the performance of the calibration approaches. The SNDI measures the level of convergence between the TLI values of a given region over the overlapping years. Figure 2 shows the interannual variability of TLI for the uncalibrated NTL data for the entire SEA region. There is a clear gap in TLI of two sensors during overlapping years in the uncalibrated NTL data. The interannual volatility within each sensor is also evident in Figure 2 (e.g. TLI from F15 takes a sudden dip after 2002), thus illustrating the necessity of inter-sensor calibration before any quantitative temporal analysis of NTL data.

Figure 3 shows the interannual variability of TLI for the NTL data post application of three calibration approaches described in section 2.2. The gap in TLI for overlapping years has reduced considerably after calibration in all three approaches. Even the interannual volatility for the same sensor has reduced significantly. The overall TLI for each sensor derived from WU2013 are significantly larger compared to the other two approaches. This pattern is partly because of the power law used (equation (2)) in calibration which unlike the other two approaches involving second order polynomials, can over-correct high raw DN values. This is consistent with Wu et al. (2013) reporting that the higher TLI values might be due to the use of a non-saturated radiance-calibrated image for calibration. The results derived using EL2014 and ZH2016 follow a similar pattern for most of the sensors except F18 sensor, for which TLI for the years 2010 and 2012 have contradictory patterns; this also reported by Zhang, Pandey, and Seto (2016) as a sensor bias for these two years. This artefact is also reflected later during SEA urban growth analysis. ZH2016 approach gives the lowest SNDI value (0.225) compared to WU2013 (0.258) and EL2014 (0.379). Hence, we selected ZH2016 calibration approach for the rest of this paper. Further, we have selected data from the latest sensor when more

than one sensor is available for a particular year, in order to reduce the discrepancy caused by sensor degradation.

3.2 Spatio-temporal analysis of urban categories

We applied the BG approach to delineate the CS, PU and CU categories from the calibrated NTL annual composites for all 15 cities. For illustration, the BG-DN scatterplot and corresponding fitted relationships are shown for Bangkok and Singapore for the year 2012 in Figure 4. The fitted polynomials are then used to obtain the DN thresholds, which are then employed to extract three urban categories. Figure 5 shows the interannual variability of CS, PU and CU categories for 15 SEA cities. Here the CS, PU and CU values for each city are normalised with the total areas (i.e. sum of CS, PU and CU). The CS (CU) category for all cities showed a decreasing (increasing) trend with time. In addition, the decreasing (increasing) trends in CS (CU) urban categories are stronger compared to the PU category, which is an indication of increasing urbanization, and can lead to a flattening in the PU category (e.g. Bangkok, Kuala Lumpur and Singapore). Generally all these 15 cities have undergone increase in urbanization (CU and PU) over time. Bangkok, Singapore and Kuala Lumpur further have a stronger urbanization trend compared to other cities since the CU category crosses the PU and CS, i.e. forming the largest category. This rapid urbanization trend can associated with the nature of these cities having developed larger metropolitans associated with rapid development when compared to other SEA cities.

3.3 Comparison of NTL urban extent with Landsat TM derived impervious area

We compared the urban categories extracted from the NTL data with the urban land use map generated from Landsat TM data for years 1994 and 2008. Landsat TM data with minimal cloud cover (<5% within the bounding box) were extracted for the eleven cities

and the two selected years, and supervised classification applied to extract the urban extent. Landsat TM data for Surabaya and Davao was not available for the year 2008 and for Manila and Medan, had more than 20% cloud cover for 2008. Hence these four cities were not included in this analysis.

Figure 6 shows spatiotemporal comparison of Landsat TM derived urban extent with NTL derived urban categories for Bangkok and Kuala Lumpur for the years 1994 and 2008. The NTL derived CU category is in good agreement with the Landsat TM derived urban land use map with the NTL high urban region consistently enveloping the Landsat TM urban extent. The difference in area between NTL and Landsat TM is expected given the different spatial resolutions (1 km for NTL vs 30 m for Landsat TM) and that the Landsat map shows the impervious surfaces (i.e. built-up areas) as opposed to lit pixels in NTL maps. Nevertheless, both maps clearly show the spatial evolution of the urban extent (NTL CU and PU categories) from 1994 to 2008. The decrease in CS and the increase in CU categories in the NTL maps are particularly evident as is the impervious surface from the Landsat map.

Figure 7 shows similar results as Figure 6 for two smaller cities Singapore and Ho Chi Minh while Figures S-1 and S-2 (supplementary material) show results for Bandung, Batam, Hanoi, Jakarta, Makassar, Phnom Penh and Yangon. As expected, urban extent maps from NTL images are unable to accurately capture inland water bodies such as lakes and rivers, and land–sea boundaries, especially when the feature sizes are comparable to the spatial resolution. To further examine the effect of land-sea boundaries, Figure 8 provides a closer view between NTL derived urban categories and Landsat TM derived land-use land-cover (LULC) classes for Singapore for the year 1994. Note that the bounding box for Singapore also includes a part of southern Johor, Malaysia. This is because Singapore is small (approx. 700 sq.km), and the southern Johor region is

influenced by Singapore's urban growth, with the urban areas of Singapore and southern Johor merging. As such the water body, primarily the narrow Johor Straits that separates Singapore from southern Johor seen in the Landsat TM LULC map is not captured in the NTL urban categorization. While spatial resolution difference is one reason (the Johore Straits is 1.3 km at its narrowest point), another reason is the saturation in NTL imagery in the highly developed areas on both sides of the Johor Straits. This indicates that NTL derived urban extents for island cities could be affected with pixel saturation and unresolved water bodies. A similar phenomena is also observed in Batam which is also an island city where saturation effects are seen along its coastline.

Figures 6 and 7 (and supplementary Figures S-1 and S-2) readily show that NTL derived core-urban (CU) extent is in overall good agreement with the Landsat derived impervious area. Figure 9 further compares the percentage of Landsat derived impervious area (expressed as a percentage of the NTL CU area) for each city with the NTL CU extent (expressed as a percentage of the total extent CS+PU+CU) for years 1994 and 2008. There is a very good correlation between the Landsat derived impervious area with NTL derived CU area. Cities such as Singapore and Bangkok which have large percentages of CU area also have large percentages in their built-up impervious surfaces. Kuala Lumpur and Ho Chi Minh have also significantly expanded (both in NTL and Landsat) between 1994 and 2008 when compared to other cities, an indication of their rapid development. Phnom Penh, Batam, Bandung, Makassar, Hanoi and Jakarta (except Yangon) have also expanded though to a lesser degree.

3.4 Analysis of NTL derived urban transitions

Transition maps for each of the 15 SEA cities were constructed to assess the spatiotemporal transitions of NTL urban categories as shown in Figure 10 and in Figures

S-4 and S-5. Pixels which changed from CS in 1994 to PU in 2008 (i.e. increasing urbanization) are denoted as “CS-PU”, and similarly for the other five transition classes seen (CS-CU, PU-PU, PU-CU, CU-CU and CU-PU). There is a low number of pixels (<1% in all cities except for 2 (Jakarta and Yangon) which had <5%) which show the reverse trend of going from a higher urbanization category to a lower (specifically CU-PU) and these are neglected below. The NTL TLI data for Yangon in year 2008 also has an unexpected dip and this would be a reason for such a reverse trend as also seen in Figure 5 for Yangon where the CU shows a broad dip.

As expected, cities which already had a larger percentage CU category (e.g., Bangkok and Singapore shown in Figure 10 and Jakarta shown in supplementary Figure S-4) in 1994 show large amounts of CU-CU pixels. Transition percentages calculated by normalizing the areas under a particular transition type with the total NTL derived urban area (i.e. sum of CU, PU and CU) in 1994 is tabulated in Table 2 for all 15 cities. It is evident that all cities have experienced significant CS-PU transitions, with values ranging from 5% for Manila to 50% for Ho Chi Minh, and with Phnom Penh, Kuala Lumpur, Hanoi, Batam and Davao also having >20% transitions. Most cities have negligible CS-CU transition with the exception of Kuala Lumpur having a 9.5% and Ho Chi Minh with 5.9%. The Indonesian cities of Batam, Medan and Makassar have large PU area in 1994 and remained so in 2008. This behaviour can be attributed to them being smaller island/coastal cities having geographical constraints (e.g., sea and/or surrounding high terrain) for expansion. The PU-CU transition was found to be highest for Ho Chi Minh followed by Kuala Lumpur and then Bangkok.

3.5 Comparison with population

We compared the urban extents extracted from NTL with population data to explore

linkages with population growth. We obtained population data from UNPD (2014) as available for years of 1995, 2000, 2005 and 2010 and for all 15 cities. Here it is noted that only NTL derived PU and CU categories were considered in this comparison as the CS is expected be sparsely populated. Figure 11 shows the comparison between the TLI (computed using PU and CU pixels) and population for all 15 cities in the 4 years of 1995, 2000, 2005 and 2010. It is observed that TLI is proportionately increasing with population except for Yangon, Manila, Kuala Lumpur and Bangkok. Yangon and Manila have their TLI not increasing proportionately with population while Kuala Lumpur and Bangkok show a stronger increases above linear. Figure 12 further shows the comparison between population and urban extent (PU and CU only) for all 15 cities for the same years. Similar results were observed as in Figure 11. Bangkok and Kuala Lumpur have significantly increased in terms of urban extent but the population has not proportionally increased.

We lastly show in Figure 13 the rate of change of NTL derived urban extent (PU+CU) versus rate of change of population over 1995-2010, normalized w.r.t. 1995. Specifically, the percentage change in urbanized land was obtained as $100 \times ((PU+CU)_{2010} - (PU+CU)_{1995}) / (PU+CU)_{1995}$ where $(PU+CU)_{1995}$ and $(PU+CU)_{2010}$ represent the combined peri-urban and core-urban areas for years 1995 and 2010, respectively. The percentage change in urbanized land ranges from 8% to >300%, with lower values for Manila and Yangon and higher values for Hanoi and Ho Chi Minh, and has a correlation r of 0.78 with rate of change of population. Inland cities such as Hanoi, Ho Chi Minh and Phnom Penh have their rapid increase in populations accompanied by a corresponding increase in urbanized land. Conversely, increase in urbanized land is not as strongly linked to increase in population for Kuala Lumpur, Singapore and Davao which are geographically constrained. It is interesting to note that the Vietnamese cities of Hanoi and Ho Chi Minh have dramatic increases in population and urbanized land over

1995-2010 which could be possibly linked to the extensive developmental activities following the post-Vietnam war era. Batam showed an even larger (416%) increase in population, this arising because it only started growing from 1995 when its population was < 200,000, and as such is not shown in Figure 13.

4. Conclusions

SEA has been going through rapid urbanization over the last few decades. In this work, we analysed urban growth patterns for 15 SEA cities using remotely sensed NTL data from 1992 to 2012. We evaluated three recently developed inter-sensor calibration approaches (WU2013, EL2014, and ZH2016) and observed that ZH2016 is best suited for the SEA region. In contrast to most prior studies on urban growth patterns that have a single arbitrary and city-specific NTL threshold, this analysis here extracted three urban categories (countryside (CS), peri-urban (PU), and core-urban (CU)) for all cities following a BG approach.

The analysis showed that NTL data together with the BG approach can successfully delineate urban categories for SEA cities. The derived core-urban and peri-urban categories compared favourably with Landsat derived impervious areas with the NTL spatial extents enveloping the impervious cover. The combined PU and CU categories were further found to increase over time for all 15 SEA cities studied. It is evident that all cities have experienced significant CS-PU transitions, with values as high as 50% for Ho Chi Minh. Most cities have negligible CS-CU transition with the exception of Kuala Lumpur and Ho Chi Minh. The Indonesian cities of Batam, Medan and Makassar have large PU area in 1994 and remained so in 2008 which can be attributed to them being smaller island/coastal cities having geographical constraints for expansion. Ho Chi Minh shows the highest PU-CU transition followed by Kuala Lumpur and Bangkok. The

complex land-sea structure of SEA region presented accuracy issues in extracting urban categories for smaller island cities such as Singapore which is also affected by narrow water bodies with size comparable to the NTL 1 km resolution.

The urbanization trends showed strong correlation with the population growth for the SEA cities with inland cities showing an unrestrained spatial growth with population. The SEA cities also expand spatially into the surrounding countryside generally following a linear trend with population increase. Extensions of this study are to analyse the urban categories at higher resolution and assess linkages with other socio-economic indicators (e.g. GDP, energy consumption) and critical infrastructures (e.g. road network, power grid and water supply).

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5. References

- Aritenang, A. F. 2014. "Urbanization in Southeast Asia: Issues and Impacts." *Bulletin of Indonesian Economic Studies* 50 (1): 144–144. doi:10.1080/00074918.2014.896312.
- Batty, M. 2007. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*. The MIT Press.
- Bhatta, B. 2010. *Analysis of Urban Growth and Sprawl from Remote Sensing Data*. Advances in Geographic Information Science. Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-05299-6.
- Burrough, P. A., R. A. McDonnell, and C. D. Lloyd. 2015. *Principles of Geographical Information Systems*. OUP Oxford.
- Cao, X., J. Chen, H. Imura, and O. Higashi. 2009. "A SVM-Based Method to Extract Urban Areas from DMSP-OLS and SPOT VGT Data." *Remote Sensing of Environment* 113 (10): 2205–2209. doi:10.1016/j.rse.2009.06.001.
- Chand, T. R. K., K. V. S. Badarinath, C. D. Elvidge, and B. T. Tuttle. 2009. "Spatial Characterization of Electrical Power Consumption Patterns over India Using Temporal DMSP-OLS Night-Time Satellite Data." *International Journal of Remote Sensing* 30 (3): 647–661. doi:10.1080/01431160802345685.
- Chen, M., H. Zhang, W. Liu, and W. Zhang. 2014. "The Global Pattern of Urbanization and Economic Growth: Evidence from the Last Three Decades." Edited by A. R. H. Montoya. *PLoS ONE* 9 (8): e103799. doi:10.1371/journal.pone.0103799.
- Doll, C. N. H., J. Muller, and J. G. Morley. 2006. "Mapping Regional Economic Activity from Night-Time Light Satellite Imagery." *Ecological Economics* 57 (1): 75–92. doi:10.1016/j.ecolecon.2005.03.007.
- Elvidge, C. D., F. Hsu, K. E. Baugh, and T. Ghosh. 2014. "National Trends in Satellite-Observed Lighting." *Global Urban Monitoring and Assessment through Earth Observation*, 97–118.
- Elvidge, C. D., D. Ziskin, K. E. Baugh, B. T. Tuttle, T. Ghosh, D. W. Pack, E. H. Erwin, and M. Zhizhin. 2009. "A Fifteen Year Record of Global Natural Gas Flaring Derived from Satellite Data." *Energies* 2 (3): 595–622. doi:10.3390/en20300595.
- Henderson, M., E. T. Yeh, P. Gong, C. Elvidge, and K. Baugh. 2003. "Validation of Urban Boundaries Derived from Global Night-Time Satellite Imagery." *International Journal of Remote Sensing* 24 (3): 595–609.
- Herold, M., N. C. Goldstein, and K. C. Clarke. 2003. "The Spatiotemporal Form of Urban Growth: Measurement, Analysis and Modeling." *Remote Sensing of Environment, Urban Remote Sensing*, 86 (3): 286–302. doi:10.1016/S0034-4257(03)00075-0.
- Imhoff, M. L., W. T. Lawrence, D. C. Stutzer, and C. D. Elvidge. 1997. "A Technique for Using Composite DMSP/OLS 'City Lights' Satellite Data to Map Urban Area." *Remote Sensing of Environment* 61 (3): 361–370. doi:10.1016/S0034-4257(97)00046-1.
- Liu, Z., C. He, Q. Zhang, Q. Huang, and Y. Yang. 2012. "Extracting the Dynamics of Urban Expansion in China Using DMSP-OLS Nighttime Light Data from 1992 to 2008." *Landscape and Urban Planning* 106 (1): 62–72. doi:10.1016/j.landurbplan.2012.02.013.
- Luo, J., and Y. H. D. Wei. 2009. "Modeling Spatial Variations of Urban Growth Patterns in Chinese Cities: The Case of Nanjing." *Landscape and Urban Planning* 91 (2): 51–64. doi:10.1016/j.landurbplan.2008.11.010.

- Ma, T., C. Zhou, T. Pei, S. Haynie, and J. Fan. 2012. "Quantitative Estimation of Urbanization Dynamics Using Time Series of DMSP/OLS Nighttime Light Data: A Comparative Case Study from China's Cities." *Remote Sensing of Environment* 124 (September): 99–107. doi:10.1016/j.rse.2012.04.018.
- Ma, T., Y. Zhou, C. Zhou, S. Haynie, T. Pei, and T. Xu. 2015. "Night-Time Light Derived Estimation of Spatio-Temporal Characteristics of Urbanization Dynamics Using DMSP/OLS Satellite Data." *Remote Sensing of Environment* 158 (March): 453–464. doi:10.1016/j.rse.2014.11.022.
- Masek, J. G., F. E. Lindsay, and S. N. Goward. 2000. "Dynamics of Urban Growth in the Washington DC Metropolitan Area, 1973-1996, from Landsat Observations." *International Journal of Remote Sensing* 21 (18): 3473–3486.
- Schneider, A., M. A. Friedl, and D. Potere. 2009. "A New Map of Global Urban Extent from MODIS Satellite Data." *Environmental Research Letters* 4 (4): 044003. doi:10.1088/1748-9326/4/4/044003.
- Schneider, A., M. A. Friedl, and D. Potere. 2010. "Mapping Global Urban Areas Using MODIS 500-M Data: New Methods and Datasets Based on 'urban Ecoregions.'" *Remote Sensing of Environment* 114 (8): 1733–1746. doi:10.1016/j.rse.2010.03.003.
- Schneider, A., C. M. Mertes, A. J. Tatem, B. Tan, D. Sulla-Menashe, S. J. Graves, N. N. Patel, et al. 2015. "A New Urban Landscape in East-Southeast Asia, 2000–2010." *Environmental Research Letters* 10 (3): 034002. doi:10.1088/1748-9326/10/3/034002.
- Seto, K. C., M. Fragkias, B. Güneralp, and M. K. Reilly. 2011. "A Meta-Analysis of Global Urban Land Expansion." *PloS One* 6 (8): e23777.
- Seto, K. C., R. Sánchez-Rodríguez, and M. Fragkias. 2010. "The New Geography of Contemporary Urbanization and the Environment." *Annual Review of Environment and Resources* 35 (1): 167–194. doi:10.1146/annurev-environ-100809-125336.
- Seto, K. C., C. E. Woodcock, C. Song, X. Huang, J. Lu, and R. K. Kaufmann. 2002. "Monitoring Land-Use Change in the Pearl River Delta Using Landsat TM." *International Journal of Remote Sensing* 23 (10): 1985–2004. doi:10.1080/01431160110075532.
- Small, C., and C. D. Elvidge. 2013. "Night on Earth: Mapping Decadal Changes of Anthropogenic Night Light in Asia." *International Journal of Applied Earth Observation and Geoinformation* 22 (June): 40–52. doi:10.1016/j.jag.2012.02.009.
- Small, C., C. D. Elvidge, D. Balk, and M. Montgomery. 2011. "Spatial Scaling of Stable Night Lights." *Remote Sensing of Environment* 115 (2): 269–280. doi:10.1016/j.rse.2010.08.021.
- Small, C., F. Pozzi, and C. D. Elvidge. 2005. "Spatial Analysis of Global Urban Extent from DMSP-OLS Night Lights." *Remote Sensing of Environment* 96 (3–4): 277–291. doi:10.1016/j.rse.2005.02.002.
- Sutton, P., D. Roberts, C. Elvidge, and K. Baugh. 2001. "Census from Heaven: An Estimate of the Global Human Population Using Night-Time Satellite Imagery." *International Journal of Remote Sensing* 22 (16): 3061–3076. doi:10.1080/01431160010007015.
- UNESCAP. 2014. *Statistical Yearbook for Asia and the Pacific 2014*. UNESCAP.
- UNPD. 2014. *United Nations, Department of Economic and Social Affairs, Population Division, World Urbanization Prospects: The 2014 Revision*.

- Wu, J., S. He, J. Peng, W. Li, and X. Zhong. 2013. "Intercalibration of DMSP-OLS Night-Time Light Data by the Invariant Region Method." *International Journal of Remote Sensing* 34 (20): 7356–7368. doi:10.1080/01431161.2013.820365.
- Zhang, Q., B. Pandey, and K. C. Seto. 2016. "A Robust Method to Generate a Consistent Time Series From DMSP/OLS Nighttime Light Data." *IEEE Transactions on Geoscience and Remote Sensing* 54 (10): 5821–5831. doi:10.1109/TGRS.2016.2572724.
- Zhang, Q., and K. C. Seto. 2011. "Mapping Urbanization Dynamics at Regional and Global Scales Using Multi-Temporal DMSP/OLS Nighttime Light Data." *Remote Sensing of Environment* 115 (9): 2320–2329. doi:10.1016/j.rse.2011.04.032.
- Zhang, Q., and K. C. Seto. 2013. "Can Night-Time Light Data Identify Typologies of Urbanization? A Global Assessment of Successes and Failures." *Remote Sensing* 5 (7): 3476–3494. doi:10.3390/rs5073476.
- Zhou, Y., S. J. Smith, C. D. Elvidge, K. Zhao, A. Thomson, and M. Imhoff. 2014. "A Cluster-Based Method to Map Urban Area from DMSP/OLS Nightlights." *Remote Sensing of Environment* 147 (May): 173–185. doi:10.1016/j.rse.2014.03.004.

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Table 1. Coordinates of the bounding box and 2015 population for each city

City	NW corner	SE corner	Population ($\times 10^3$ people)
Bandung (BDO)	-6.76° 107.41°	-7.11° 107.88°	2,544
Bangkok (BKK)	14.26° 100.19°	13.53° 100.89°	9,270
Batam (BTH)	1.18° 103.88°	1.01° 104.14°	1,391
Davao (DVO)	7.34° 125.46°	7.00° 125.70°	1,630
Ho Chi Minh (HCM)	11.16° 106.35°	10.61° 106.96°	7,298
Hanoi (HAN)	21.36° 105.53°	20.85° 106.12°	3,629
Jakarta (JKT)	-5.92° 106.34°	-6.78° 107.28°	10,323
Kuala Lumpur (KUL)	3.42° 101.25°	2.74° 101.87°	6,837
Medan (MDN)	3.81° 98.44°	3.45° 98.88°	2,204
Makassar (MKS)	-5.00° 119.38°	-5.20° 119.56°	1,489
Manila (MNL)	14.86° 120.84°	13.91° 121.24°	12,946
Phnom Penh (PNH)	11.66° 104.75°	11.45° 104.97°	1,731
Singapore (SIN)	1.71° 103.49°	1.23° 104.04°	5,619
Surabaya (SUB)	-7.06° 112.36°	-7.72° 112.84°	2,853
Yangon (RGN)	17.02° 96.01°	16.76° 96.28°	4,802

Table 2. Transition percentages obtained using ZH2016 and calculated as the area of a transition region normalized by the NTL derived total area (CS+PU+CU) for 1994 year

City	Transition as proportion of total area (%)				
	CS-PU	CS-CU	PU-PU	PU-CU	CU-CU
BDO	6.92	0.00	26.57	0.80	7.06
BKK	11.45	0.00	22.37	10.88	28.26
BTH	32.52	0.81	28.62	4.72	2.60
DVO	31.99	0.00	23.02	5.10	2.11
HCM	50.49	5.93	4.51	20.37	5.16
HAN	24.42	0.00	7.32	2.24	1.75
JKT	5.94	0.49	24.97	3.13	15.58
KUL	32.59	9.46	9.46	19.11	16.79
MDN	5.97	0.00	27.14	1.74	6.18
MKS	18.98	0.00	39.04	4.01	9.09
MNL	4.97	0.00	28.36	1.48	13.85
PNH	40.52	1.31	16.01	7.52	4.25
SIN	17.21	0.85	15.82	10.26	30.64
SUB	11.95	0.00	23.34	3.64	6.20
RGN	10.30	0.00	34.37	0.12	11.79

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