EFFECT OF URBAN FORMS: TOWARDS THE REDUCTION OF CO2 EMISSIONS

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ABSTRACT

For the past few decades, urbanization has been occurring at a rapid pace. The relationship between urban density and energy consumption, which are accompanied by emissions of greenhouse gases, is still not conclusive. This study examined the relationship between urban form and carbon dioxide (CO_2) emissions from urban areas in 50 cities in Japan. We employed satellite imagery to delineate urban areas. The maps of administrative boundary were used to clip urban regions from each scene of satellite image. The clipped images were classified into a binary class: urban built-up and others. The sectoral data for the CO_2 emissions at municipal level in 2005 was obtained from various sources. We examined two types of approaches to quantify urban forms. One method involved landscape metrics, which included two types of metrics, compactness and complexity. The other method is a new method and it relies on quantifying the reduction rate of urban areas from the city center by applying ring-shaped buffers. We called this method the buffer compactness index. Results indicated that there are correlations between several indices of urban forms and sectoral CO_2 emissions.

INTRODUCTION

Urban population has been increasing especially in developing countries (UN, 2007). In the year 2005, about half of the world's population lived in urban areas, and projections show that this percentage will increase to 60% by 2030 (UN, 2007). Urban contributes to 67% and 71% to the global primary energy demand and energy-related CO_2 emissions respectively for the year 2006 (WEO, 2008). Thus, the urban development path is a critical factor in determining the energy use and the accompanying emissions of greenhouse gases (Dhakal, 2008), and better urban design could reduce carbon emissions (Marshall, 2008). Several studies examined the relationship between urban form and urban transport energy use (Breheny, 1995; Mindali, et al., 2004; Rickwood et al., 2008) and the associated Carbon dioxide (CO_2) emissions (Anderson et al., 1996; Reckien et al., 2007). However, the relationships between urban form and energy consumption from transportation are still not conclusive, and most studies employ population density as the measurement of urban form. However, such fine population density maps are not always available. More comprehensive ways to measure the urban form are needed.

Spatial metrics, known as landscape metrics, are commonly used in landscape ecology (Gustafson, 1998) as a quantitative measure to characterize urban forms (Herold et al., 2002; Herold et al., 2003; Huang et al., 2007). Landscape metrics is used to quantify spatial shapes and patterns among patches in the landscape (O'Neill et al.,1988; McGarigal et al., 2002). A patch can be defined as "a contiguous group of cells of the same mapped category" (Turner et al., 2001). In this study, we will examine various spatial metrics and a new method to characterize urban forms. In Japan, CO_2 emissions at the municipal level are available for the whole nation. By using this data, we present a statistical model that establishes a relationship between CO_2 emissions per capita and socio-economic and spatial variables which characterize Japanese cities.

MATERIALS AND METHODS

Urban Extent

For the study we selected 50 small to medium-sized cities in Japan. These cities were selected based on the following criteria: 1) population ranged from 80,000 to 450,000 so that the cities would be small enough to be independent to the neighboring cities and large enough to contain commercial areas, 2) cities that are located beyond commuting distance of metropolitan areas such as Tokyo, Nagoya and Osaka. These 50 urban areas were delineated based on remotely sensed imagery. In this study, Landsat ETM+ imagery of 1999, 2000, 2001 and 2002 with spatial resolution of 30 m at six bands, 1, 2, 3, 4, 5 and 7, was used. Firstly, each city was spatially extracted by vector format map of the administrative boundary. The supervised classification method, based on the maximum likelihood algorithm, was applied to the clipped images, and the images were classified into six classes: urban/built-up, crop field, forest, grass land, barren/sandy lands and water body. The classified images have been converted into binary images: urban built-up and others, and a 3x3 majority filter was applied to remove isolated or noise pixels. A majority filter applies a moving window by passing through the classified data and majority class within the window is determined (Lillesand et al., 2004).

The land use data at a scale of 100 m grids (1/10 subdivision of standard mesh of the Japanese Standard Mesh System) of Digital National Land Information (DNLI) was used as reference data. The confusion matrix method was used to assess the accuracy of the classified image. The confusion matrix can provide the basis to describe both classification accuracy and characterize errors (Foody, 2002). One of most popular measures that is derived from a confusion matrix is the overall accuracy or percent correctly classified (PCC) (Foody, 2002). PCC is calculated by the ratio of the sum of correctly classified sub-pixels in all classes to the sum of the total number of sub-pixels (Lillesand et al., 2004). User's accuracy and producer's accuracy are descriptive measures that can be obtained from the confusion matrix. User's accuracy indicates the probability that a pixel classified into a given category actually represents that category on the ground, and producer's accuracy indicates how well training set pixels of the given cover type are classified (Lillesand et al., 2004). In this study, the confusion matrix was determined by random sampling of 300 points with minimum 100 points for each class. The matrix compared the relationship between known reference data (obtained through ground truthing) and the corresponding results of a category-by-category basis classification (Lillesand et al., 2004). All image processing works and accuracy assessment were implemented in ERDAS IMAGINE 9.3(ERDAS Inc.) and ArcGIS 9.2 (ESRI Inc.).

Urban Form Index

This study examines spatial metrics and a new method to quantify urban forms. One method employs spatial metrics, known as landscape metrics. The landscape metrics are quantitative indices to describe landscape structures and patterns. (McGarigal and Marks, 1995). In this study, the metrics were used to describe urban structures. Four metrics that represent two dimensions of the urban forms, compactness and complexity (Huang et al., 2007), were examined (Figure 1, Table 1). The large value of the Compactness Index (CI) indicates that the patch shapes tend to be regular and fewer patches. Compactness Index of the Largest Patch (CILP) represents the overall shape of the largest patch, which usually an urban center. The large value of Area Weighted Mean Shape Index (AWMSI) indicates that the shapes of patches are more irregular. Here, regular patch shape represents more circular, and irregular patch shape represents more edges and less interior area (Farina, 2006). Area Weighted Mean Patch Fractal Dimension (AWMPFD) describes the raggedness of the shapes and its value approaches one for simple perimeters and approaches two for more complex perimeters. These urban form indices were computed using a custom code written in the Interactive Data Language (IDL) software.

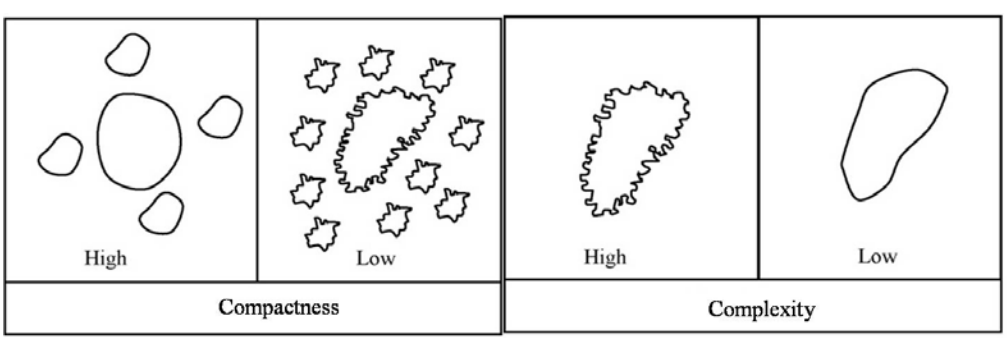

Figure 1. Schematic map of spatial metrics (Huang et al., 2007).

Table 1. Spatial metrics

	Indicators	Abbreviation	Formula
Compactness	Compactness Index	CI	$CI = \frac{\sum_i P_i / p_i}{N^2} = \frac{\sum_i 2\pi\sqrt{a_i/\pi} / p_i}{N^2}$
	Compactness Index of the Largest Patch	CILP	$CILP = \frac{2\pi\sqrt{a/\pi}}{p}$
Complexity	Area Weighted Mean Shape Index	AWMSI	$AWMSI = \sum_{j=1}^{n}\left[\left(\frac{0.25 p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$
	Area Weighted Mean Patch Fractal Dimension	AWMPFD	$AWMPFD = \sum_{j=1}^{n}\left[\left(\frac{2\ln(0.25 p_{ij})}{\ln a_{ij}}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$

The descriptions of the above equations are as follows:

CI: where *ai* and *pi* are the area and the perimeter of patch *i*, *Pi* is the perimeter of a circle with the area of *ai* and *N* is the total number of patches (Li and Yeh, 2004; Huang et al., 2007),

CILP: where *a* and *p* are the area and perimeter of largest patch (Huang et al., 2007),

AWMSI and AWMPFD: where *pij* is the perimeter of patch *ij* and *aij* is the area of patch *ij* (*i*= number of patch types, *j*= number of patches) (McGarigal and Marks, 1995).

The other index was derived from the percentage of urban area within the ring buffers from the urban center. The center of the urban area was determined by the following procedures. First, a 5x5 majority filter was applied to the urban/non-urban image. Based on a preliminary study, this 5x5 majority filter enables to avoid creating two large polygons separated by any physical features such as a river. Once the largest polygon was selected, a xy coordinate of the centroid was obtained. Then, the multiple ring buffers of 1km width are created from the center of the urban area towards the exterior. The buffers are clipped by the city boundaries and the outermost buffers are 15km from the center (Figure 2). The percentage of urban area within each buffer was calculated. The reduction rate of urban area has been quantified using the inverse value of the slope (also called the regression coefficient) of the regression line. This reduction rate is considered as the indicator of compactness. The larger the value of the indicator the more compact the city is, the smaller the value there is more of an urban sprawl. We called this index as buffer compactness index (BCI) (equation (1)).

$$BCI = -\frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2} \tag{1}$$

where *x* is a buffer radius and *y* is the percentage of urban area within the buffer.

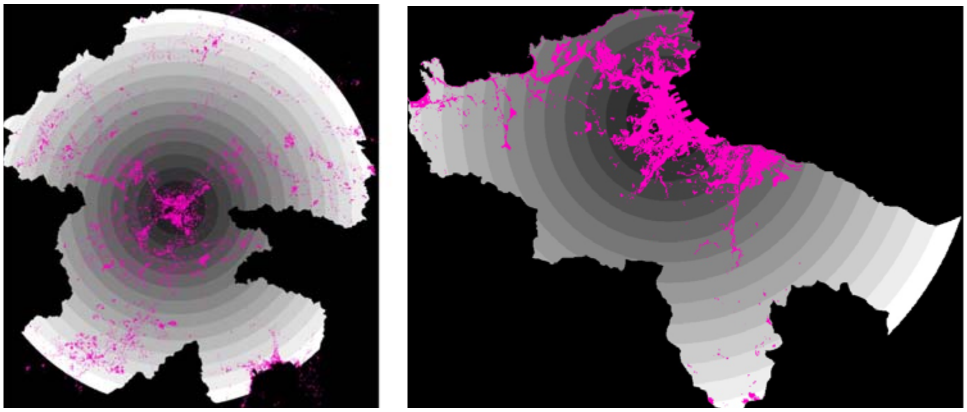

Figure 2. 1km radius buffers overlayed with urban extent, Higashi Hiroshima (left): BCI = 2.11 (population 17.5 million), Otaru (right): BCI = 4.94 (population 15 million).

Other Data and the Statistical Test

In addition to the physical structure of cities, two socio-economic variables, average per capita income and population in 2005, were also employed. The data for the Carbon dioxide (CO_2) emission at municipal level in 2005 was obtained from a number of sources for four sectors: industrial (Nansai et al., 2004; GIO, 2009), commercial (Tonooka et al., 2008), residential (Tanaka et al., 2008) and transportation (Yonezawa and Matsuhashi, 2009). The transportation sector consists of passenger transportation and freight transportation considered separately.

The socio-economic and spatial variables served as independent variables to test their influence on the CO_2 emissions per capita. The method employed was a stepwise multiple linear regression analysis, preceded by a coefficients' correlation test. In order to avoid multicollinearity, the variables that are strongly correlated to other variables were removed (Table 2). CILP is strongly correlated to AWMSI and AWMPFD (with a value of -0.85), and AWMSI is strongly correlated to BCI (with a value of 0.63) and AWMPFD (0.9). By excluding CILP and AWMSI, the independent variables used for the analyses are average per capita income, population, BCI, CI and AWMPFD, and the dependent variables are CO_2 emission per capita from five sectors.

Table 2. Correlation analysis among spatial metrics (*N*=50)

	BCI	CI	CILP	AWMSI	AWMPFD
BCI	1.00				
CI	-0.07	1.00			
CILP	-0.51	0.06	1.00		
AWMSI	0.63	0.06	-0.85	1.00	
AWMPFD	0.49	0.23	-0.85	0.90	1.00

RESULTS AND DISCUSSION

Based on the confusion matrix of 50 cities, the average PCC is 88.1, and average producer's accuracy of urban class is 74.5 and the user's accuracy is 93.7. These relatively high percentages indicate good classification results and show the possibility of urban extent delineation from remotely sensed imagery.

The result of analysis shows some correlation between CO_2 emissions and spatial metrics (Table 3). The result of stepwise multiple linear regression analysis indicates that CO_2 emissions from all sectors except freight transportation sector are predicted by some of urban form indices (Table 4). The low correlation coefficient and low R square indicate there are some correlations between CO_2 emissions and urban form index, but not strong. For industrial sector, AWMPFD is significant at the 95% confidence level. For the commercial sector, CI and AWMPFD are significant at the 95% confidence level. For residential sector, GDP and BCI are significant at the 95% confidence level. For passenger transportation sector, CI is significant at the 95% confidence level. AWMPFD is inversely correlated to CO_2 emissions at industrial and commercial sectors which implies the less complex shape (more circular) of urban area the more CO_2

emission for these sectors. BCI has positive correlations with CO2 emissions of the residential sector, which indicates the more compact the more CO2 emissions of residential sector. Another result is the negative correlations between CI and CO2 emission of passenger transportation. This result indicates that the more compact the city the less CO2 emission from passenger transportation.

Table 3. Correlation analysis between CO2 emission at each sector and spatial metrics (*N*=50)

		BCI	CI	AWMPFD
CO2 emission per capita	Industrial	-0.23	-0.13	-0.40
	Commercial	-0.03	0.16	-0.18
	Residential	0.44	-0.21	0.00
	Passenger transportation	-0.15	-0.30	-0.19
	Freight transportation	0.01	0.10	-0.14

Table 4. Coefficients of stepwise multiple linear regression analysis

	Coefficients	Standard Error	t value	Pr(>|t|)	R square
Industrial sector					0.156
AWMPFD	-6.292	2.112	-2.979	0.0045	
Commercial sector					0.120
Population	1.19E-06	8.27E-07	1.434	0.1584	
CI	2.50E+02	1.18E+02	2.126	0.0389	
AWMPFD	-5.02E+00	2.27E+00	-2.209	0.0322	
Residential sector					0.284
GDP	-4.31.E-04	1.80.E-04	-2.391	0.0209	
BCI	1.05.E-01	2.47.E-02	4.253	9.97E-05	
Transportation sector (Passenger)					0.142
Population	-3.26E-07	1.93E-07	-1.687	0.0982	
CI	-8.15E+01	3.11E+01	-2.625	0.0117	
Transportation sector (Freight)					0.050
GDP	-3.82.E-04	2.39.E-04	-1.597	0.117	

CONCLUSIONS

This study examined various methods to characterize urban forms and investigated the relationship between CO2 emissions from four sectors and socio-economic and spatial variables. Urban extent maps were created using remotely sensed imagery, and the maps achieve quite high classification accuracy. Two types of methods were employed to quantify urban forms. One method involved landscape metrics, which included two dimensions of urban metrics, compactness and complexity which each of them containing two indicators. The other method, a new one, quantified the reduction rate of urban areas from the city center by applying ring-shaped buffers. Thus, total five indicators, CI, CILP, AWMSI, AWMPFD and BCI, were examined. The results of correlation and regression analyses indicated that some of the urban form indices had a significant correlation to CO2 emissions. Compactness Index (CI) was found to be a significant variable in predicting CO2 emission of passenger transportation sector. This inverse relationship suggests that compact cities emit less CO2 emission from passenger transportation sector than sprawled city. The index used in this study could be used as indicator of low carbon cities that emit less CO2 from transportation. Also, this study found proof to support the hypothesis that the less complex the shape (more circular) of an urban area, the more CO2 emissions come from commercial and industrial sectors and the hypothesis that the more compact the more CO2 emissions come from the residential sector. However, more research is needed to conclude on the actual strength of the deterministic relationships.

In this study, we limited the size of our study areas from smaller to medium sized cities to allow for an examination of cities with similar conditions. For future study, we will include more sizes of cities in Japan, and possibly also extend our study to cities outside Japan. Although availability of urban maps varies according to region, the urban extent map from remotely sensed imagery can be obtainable anywhere in the world. Although five urban form indices showed correlations to CO2 emissions, the correlations are not strong. We need to investigate more indices that characterize urban forms.

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