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Relationship between urban form and CO_2 emissions: Evidence from fifty Japanese cities

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This study examined the relationship between urban form and carbon dioxide (CO_2) emissions from urban area in fifty cities in Japan. The digital maps of administrative boundary were used to clip urban regions from scenes of the satellite images. The clipped images were classified into a binary class: urban built-up and others. The sectoral data for the CO_2 emissions at the municipality level in 2005 were obtained from published sources. We used two types of approaches to quantify urban forms. The first method involved landscape metrics which describe compactness and complexity of settlement patches. Second method, which we developed, quantifies the reduction rate of urban area from the city center by applying ring-shaped buffers. The results indicated that there were correlations between spatial indices of urban form and sectoral CO_2 emissions for the residential and passenger transport sectors. The inverse relationship between the compactness index and CO_2 emissions in our study suggest that less fragmented and compact cities emit less CO_2 from the passenger transportation sector than the sprawled cities. Our study indicates that less complex cities lower residential per capita CO_2 emissions but too dense settlements in mono-centric form may lead to greater per capita CO_2 emissions. Complexity seems to have less significant for CO_2 emissions in general. Our research also favors a high income, smaller population size and denser city for lower CO_2 emissions.

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1. Introduction

Urban population has been increasing for several decades at an accelerated pace (World Urbanization Prospects and Revision, 2009). In 2009, about half of the world's population (3.42 billion out of 6.83 billion) lived in urban area, and projections show this will increase to 68.7% by 2050 (World Urbanization Prospects and Revision, 2009). One estimate showed urban area contributed 67% and 71% to the global primary energy demand and energy-related CO_2 emissions respectively for 2006 (World Energy Outlook, 2008). Thus, urbanization and urban development are critical factors for CO_2 emissions and mitigation (Dhakal, 2008; Poumanyvong and Kaneko, 2010; C. O'Neill et al., 2010). Better urban design has potentials to influence energy consumption and carbon emissions (Marshall, 2008; Chen et al., 2011; Madlener and Sunak, 2011). Several studies have examined the relationship between urban form and urban transport energy use (Breheny, 1995; Mindali et al., 2004; Rickwood et al., 2008), between buildings and transport (Steemers, 2003) and the associated carbon dioxide (CO_2) emissions Anderson et al., 1996; Reckien et al., 2007 in the past. However, the relationship between urban form and energy consumption and CO_2 emissions from even transportation is still not conclusive for different density thresholds while the empirical evidences of how transport and buildings work together to affect energy and CO_2 emissions are not well-established. The studies on urban form and urban energy use and CO_2 emission at urban scale (not individual sectors) are limited. In addition, most studies employ population density as a measure of urban form. Average urban population density alone is not enough to represent urban form. More comprehensive ways to represent urban form, especially its spatial configuration, and their relations with energy use and CO_2 emissions and mitigations 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, 2003; Huang et al., 2007). Landscape metrics are used to quantify spatial shapes and patterns among patches in the landscape (O'Neill et al., 1988; McGarigal et al., 2002) and rarely used in relation to energy and CO_2. Recently one study estimated the relationship between urban forms and energy consumption in the Pearl River Delta in China (Chen et al., 2011). In landscape metrics approach, a patch can be defined as "a contiguous group of cells of the same mapped category" (Turner et al., 2001). In this study, we examined various spatial metrics and used methods to characterize urban form. Our indices dealt with (a) the shape and the fragmentation of urban settlement patches in cities, (b) the density of urban settlement patches, (c) the extent of irregularly or roughness of the perimeter of settlement patches, (d) the extent of concentrated mono-centric settlements and (e) population density. In Japan, CO_2 emissions at the municipal level are available for the whole nation from past studies. By using this data and landscape metrics, we analyzed relationships between sectoral, i.e. household, transport and commercial CO_2 emissions and the socio-economic and spatial variables that characterize Japanese cities' urban form. Such relationships have important policy implications for designing low carbon cities in Japan where the carbon mitigation approach of cities' policies has been transfixed largely around the scale of activities and the technologies, and insufficiently to the spatial and physical re-organization of cities. We hope this study will contribute to the debate of urban form and CO_2 relations and to create a better understanding on the implications of the spatial form in low carbon urban development.

2. Method and data

The method used in this study has several steps. The first step was to select the cities to be analyzed. Cities with similar socio-economic attributes were selected and cities with attributes that constrained to demonstrate the effect of urban form such as large differences in population size, economic structure, income, and city location were discarded. The second step was the collection of total and sectoral CO_2 emissions of cities. The third step was to use the remote sensing technique to delineate the urban area from satellite imagery to take into account the physical attributes of the settlement patches in cities and to use it for developing spatial indices of urban form. The fourth step was to quantify urban form indices and carry out correlation analyses of indices with CO_2 emissions.

2.1. Selection of study area

Japan's total Green House Gases (GHGs) emissions in fiscal year 2008 were 1282 million tons of CO_2e. The Japanese government has set ambitious targets of GHG mitigation. Its law has mandated cities to prepare climate change mitigation action plans to actively pursue carbon mitigation. For this study, we selected 50 small to medium-sized Japanese cities. These cities were selected based on the following criteria: (1) population range of 80,000–450,000 so that the cities would be small enough to be independent from the neighboring cities and large enough to contain commercial areas, (2) cities that were located beyond the commuting distance of large metropolitan areas such as Tokyo, Nagoya and Osaka to negate the effects of being a satellite-city of large cities and (3) cities that were not knows as "industrial" because industrial cities could produce large CO_2 emissions relative to other sectors and could hamper our effort to see the impacts of urban form. One of our key efforts was also to select cities where income differences were not very big because income and CO_2 emissions could be strongly correlated. This might be an issue when comparing cities in developing and developed countries, but our analyses of Japanese cities showed less income disparity among cities. The mean annual income per capita of these fifty cities was 1187,000 yen (annual average exchange rate of 1 US$ in 2005 was 110 yen) with standard deviation of 27,000 yen in 2005 (Municipal taxes and adjustment, 2005). The name of cities and other details are shown in the Appendix.

2.2. Development of urban extent map

In this study urban areas were delineated based on remote sensed imagery. We used 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.[1] 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. The images were classified into six classes: urban/built-up, crop field, forest, grass land, barren/sandy lands and water body. The classified images were converted into binary images: urban built-up and others, and a 3×3 majority filter was applied to remove the isolated or noise pixels. A majority filter uses a moving window by passing through the classified data and the majority class within the window is determined (Lillesand et al., 2004).

The land-use data on 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 for both describing classification accuracy and characterizing errors (Foody, 2002). One of the most popular measures derived from a confusion matrix is the overall accuracy or Percent Correctly Classified (PCC) Foody, 2002. The PCC is calculated as 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 a minimum of 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 work and accuracy assessment were carried out in ERDAS IMAGINE 9.3(ERDAS Inc.) and ArcGIS 9.2 (ESRI Inc.).

[1] In this study, 2005 CO2 emission data is correlated but the satellite imagery of previous years are used. The Landsat 7 ETM+ experienced a failure of its Scan Line Corrector (SLC) on May 2003, and we had to select the best image for each city from 1999 to 2003 in order to avoid the cloud cover in the satellite imagery. Japanese cities are relatively matured-cities in terms of urban expansion.

2.3. Indices of urban form

This study examined previously developed spatial metrics and also presented a new method to represent urban form. The method employs spatial metrics that are derived from the landscape metrics. The landscape metrics are quantitative indices to describe "landscape" structures and patterns (McGarigal and Marks, 1995). Four metrics represent two dimensions of the urban forms, the compactness and the complexity (Huang et al., 2007; McGarigal and Marks, 1995) (Fig. 1, Table 1). It covers three aspects: the shape of the individual settlement patch, the extent of fragmentation or sparseness of settlement patches, and the extent of irregularity of the perimeter of settlement patches. In addition to the existing indices (Huang et al., 2007; McGarigal and Marks, 1995; Li and Yeh, 2004), our new method – Buffer Compactness Index – account for the density gradient of urban settlement from the city center (this is useful for Japanese cases where cities tend to have a central core) as well as population density.

The large value of the Compactness Index (CI, see Table 1) indicates that the settlement patches' "shape" tends to be regular and the "number" of patches is fewer. Thus, higher CI means less fragmented and more regular urban settlement patches. The Compactness Index of the Largest Patch (CILP, see Table 1) represents the overall shape of the largest settlement patch, which is usually an urban center. The urban complexity is characterized by the roughness of the settlement perimeter. The larger value of Area Weighted Mean Shape Index (AWMSI, see Table 1) indicates that the shapes of patches have more irregular perimeter or that the urban settlements are more complex. Here, regular patch shape represents a more circular shape, and irregular patch shape represents more edges and less interior area (Farina, 2006). The Area Weighted Mean Patch Fractal Dimension (AWMPFD, see Table 1) 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.

As mentioned above, another index was developed in this study 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 5×5 majority filter was applied to the urban/non-urban image. Based on a preliminary study, this 5×5 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 $x\,y$ coordinate of the centroid was obtained. Then, multiple ring buffers of 1 km width were created from the center of the urban area towards the exterior. The buffers were clipped by the city boundaries and the outermost buffers were 15 km from the center (Fig. 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 (or sprawl) in monocentric form of city settlements. This gives an indication of how far a city is sprawled from central business areas and how dense they are at various distances from the city core. The larger the value of the indicator the more compact and monocentric the city is, the smaller the value there is more of an urban sprawl. We called this index Buffer Compactness Index (BCI) (Eq. (1)). Fig. 2 shows the urban settlement extent of two cities in a 1 km radius buffer as an illustration,

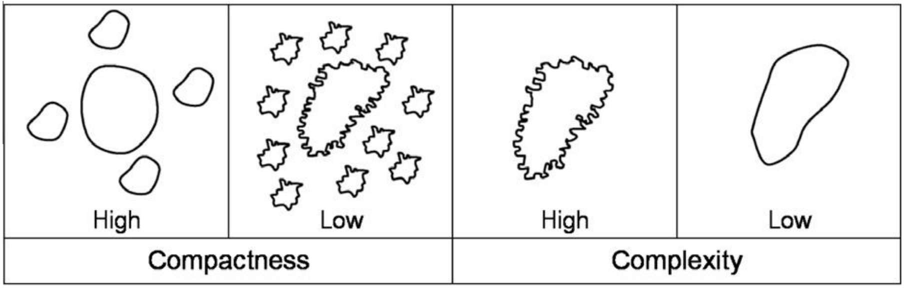

Fig. 1. Schematic map of spatial metrics (Huang et al., 2007).

Table 1
Spatial metrics.

	Indicators	Abbreviation	Formula
Compactness	Compactness index	CI	$\mathrm{CI} = \frac{\sum_i P_i/p_i}{N^2} = \frac{\sum_i 2\pi\sqrt{a_i/\pi/p_i}}{N^2}$
	Compactness index of the largest patch	CILP	$\mathrm{CILP} = \frac{2\pi\sqrt{a/\pi}}{p}$
Complexity	Area weighted mean shape index	AWMSI	$\mathrm{AWMSI} = \sum_{j=1}^{n}\left[\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n}a_{ij}}\right)\right]$
	Area weighted mean patch fractal dimension	AWMPFD	$\mathrm{AWMPFD} = \sum_{j=1}^{n}\left[\left(\frac{2\ln(0.25p_{ij})}{\ln a_{ij}}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n}a_{ij}}\right)\right]$

The descriptions of the above equations are as follows:
CI: where a_i and p_i are the area and the perimeter of patch i, P_i is the perimeter of a circle with the area of a_i 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 the largest patch (Huang et al., 2007).
AWMSI and AWMPFD: where p_{ij} is the perimeter of patch ij, and a_{ij} is the area of patch ij (i = number of patch types, j = number of patches) (McGarigal and Marks, 1995).

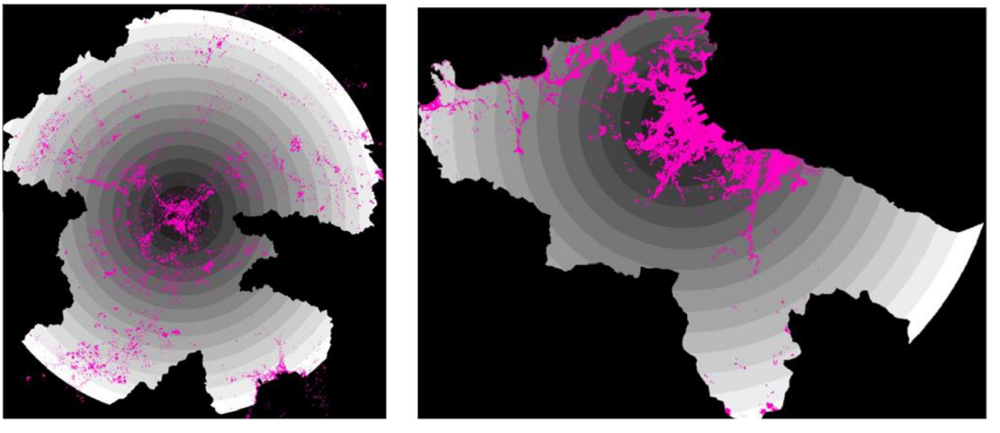

Fig. 2. One km radius buffers overlayed with urban extent, Higashi Hiroshima City (left): BCI = 2.11 (population 175,000), Otaru City (right): BCI = 4.94 (population 150,000).

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

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

In addition to the physical structure of cities, four variables that might have strong impact on CO_2 emissions and energy consumptions were examined. These variables are average per capita income, city population size, average temperature, and average urban area per capita (the opposite of population density). The total urban area in each city was derived based on the urban extent map, and the area was divided by the population to obtain the average urban area per capita (not the average of the city as a political unit). Data for all four variables are for the year 2005.

These socio-economic and spatial variables served as independent variables to test their influence on CO_2 emissions per capita. The data for CO_2 emissions in 2005 were obtained based on studies by Yamagata and Nakamichi (2009). They integrated researches to estimate sectoral CO_2 emissions at the municipal level for the whole nation from residential (Tanaka et al., 2008), commercial (Tonooka, 2008), industrial (Nansai et al., 2004; Green House Gas Inventory Office in Japan, 1990) and transportation (Yonezawa and Matsuhashi, 2009; Kudoh et al., 2005). The data for CO_2 emissions for passenger transportation (mainly car) and freight were used from the study of Yonezawa and Matsuhashi (2009).

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

2.4. Statistical test

The method employed in this study was a stepwise multiple linear regression analysis proceeded by a coefficients' correlation test. In order to avoid multi-collinearity, the variables that were strongly correlated to other variables were removed (Table 2). CILP was strongly correlated to AWMSI and AWMPFD (with a value of −0.85), and AWMSI was strongly correlated to BCI (with a value of 0.63) and AWMPFD (0.9). Therefore, we excluded CILP and AWMSI. The independent variables used for further analyses were average per capita income, population, average temperature, and average urban area per capita (of city admin. boundary), BCI, CI and AWMPFD, and the dependent variables were CO_2 emissions per capita from various sectors (Table 3).

3. Results and discussions

Based on the confusion matrix of 50 cities, the average PCC is 88.1%, and the 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 remote sensed imagery in an accurate way. Details of cities are shown in the Appendix.

The result of the correlation analysis shows a weak correlation between CO_2 emissions and spatial metrics (Table 4). The result of the stepwise multiple linear regression analysis indicates that CO_2 emissions from all sectors are predicted by some of the urban form indices (Table 5). Relatively high values of adjusted R square are observed for CO_2 emissions per capita from the residential ($R^2 = 0.6$) and passenger transport (mostly car) ($R^2 = 0.43$) sectors. For other sectors, the values of adjusted R square are low ($R^2 = 0.04 \sim 0.18$), meaning that the percentage of the variation in CO_2 emissions per capita from industrial, commercial and freight transport sectors that are explained by the variation in the BCI, CI and AWMPFD, are low in the regression model. We must also recall that our selected cities do not have a strong presence of industry sector. No noticeable influence of urban form indices on commercial CO_2 emissions was a surprise, but it can be possibly explained by few possible facts, e.g.

Table 3
Independent and dependent variables.

	Indicators	Abbreviation
Independent variables	Buffer compactness index	BCI
	Compactness index	CI
	Area weighted mean patch fractal dimension	AWMPFD
	Average income per capita in 2005	Income
	Population in 2005	Pop
	Average temperature in 2005	AveTemp
	Urban area per capita (city admin. boundary)	Urban
Dependent variables	Industrial sector	Indus CO2
Annual CO2 emissions per capita in 2005 from	Commercial sector	Comm CO2
	Residential sector	Resi CO2
	Transportation sector	Trans CO2
	Passenger transport	PassCar CO2
	Freight transport	FreiCar CO2

Table 4
Correlation analysis between CO2 emissions per capita of each sector and spatial metrics ($N = 50$).

	BCI	CI	AWMPFD	Adjusted R^2
Indus CO2	−0.228	−0.134	−0.395	0.1688
Comm CO2	−0.035	0.163	−0.176	0.0410
Resi CO2	0.442	−0.196	−0.001	0.6023
Trans CO2	−0.058	−0.017	−0.214	0.1838
Pass Car CO2	−0.146	−0.301	−0.187	0.4381
Frei Car CO2	0.010	0.094	−0.144	0.0505

the commercial sectors are invariably concentrated in the central areas of cities, the scale of activities of the commercial sector is smaller, and others.

The analysis shows that a higher level of regularity of urban settlement shape and compactness of urban settlements (represented by CI) lead to lower residential CO_2 emissions, but the effect of urban complexity on residential CO_2 emissions is negligible. On the contrary, the analysis shows that a higher BCI leads to greater CO_2 per capita from the residential sector, indicating that the city with monocentric dense settlement might lead to greater per capita residential CO_2 emissions. For CO_2 emissions from the passenger transport sector, our analysis endorses commonly held views that higher regularity in shape of urban settlements and higher density of settlements lead to lower per capita emissions (Table 4). Table 4 also shows that a greater urban complexity leads to reduced passenger car transport CO_2 emissions which are possible if travel activities do not cater to the complex edges of the cities. However, as the results of stepwise regression analysis showed (Table 5), only the BCI is a significant variable among the spatial metrics.

Our analyses point an important distinction between representing urban form by simply average population density vs spatial determinants of urban form such as CI and BCI. Average population

Table 5
Coefficients of stepwise multiple linear regression analysis ($N = 50$).

	Coefficients	Standard error	t Value	Pr (>|t|)	Adjusted R^2
Indus CO2					0.1688
AveTemp	0.05132	0.03083	1.665	0.102631	
AWMPFD	−6.5093	2.07711	−3.134	0.00297	**
Comm CO2					0.0410
CI	158.267	100.005	1.583	0.1202	
AWMPFD	−2.839	1.717	−1.654	0.1048	
ResiCO2					0.6023
Income	−3.72E-04	1.36E-04	−2.728	0.00906	**
Pop	6.29E-07	2.85E-07	2.204	0.03268	*
AveTemp	−6.23E-02	9.76E-03	−6.383	8.42E-08	***
BCI	3.55E-02	2.33E-02	1.526	0.13393	
Trans CO2					0.1838
CI	119.5697	72.2533	1.655	0.104615	
Urban	1.0118	0.2804	3.608	0.000746	***
PassCar CO2					0.4381
Income	1.99E-04	9.90E-05	2.006	0.05099	
Pop	3.26E-07	2.01E-07	1.62	0.11247	
AveTemp	−2.53E-02	7.00E-03	−3.619	0.00076	***
BCI	−5.11E-02	1.63E-02	−3.14	0.00302	**
Urban	4.48E-01	1.04E-01	4.307	9.14E-05	***
FreiCar CO2					0.0505
CI	119.281	75.8287	1.573	0.12242	
Urban	0.6016	0.2943	2.044	0.046578	*

* Correlation is significant at the 0.05 level (two-tailed).
** Correlation is significant at the 0.01 level (two-tailed).
*** Correlation is significant at the 0.001 level (two-tailed).

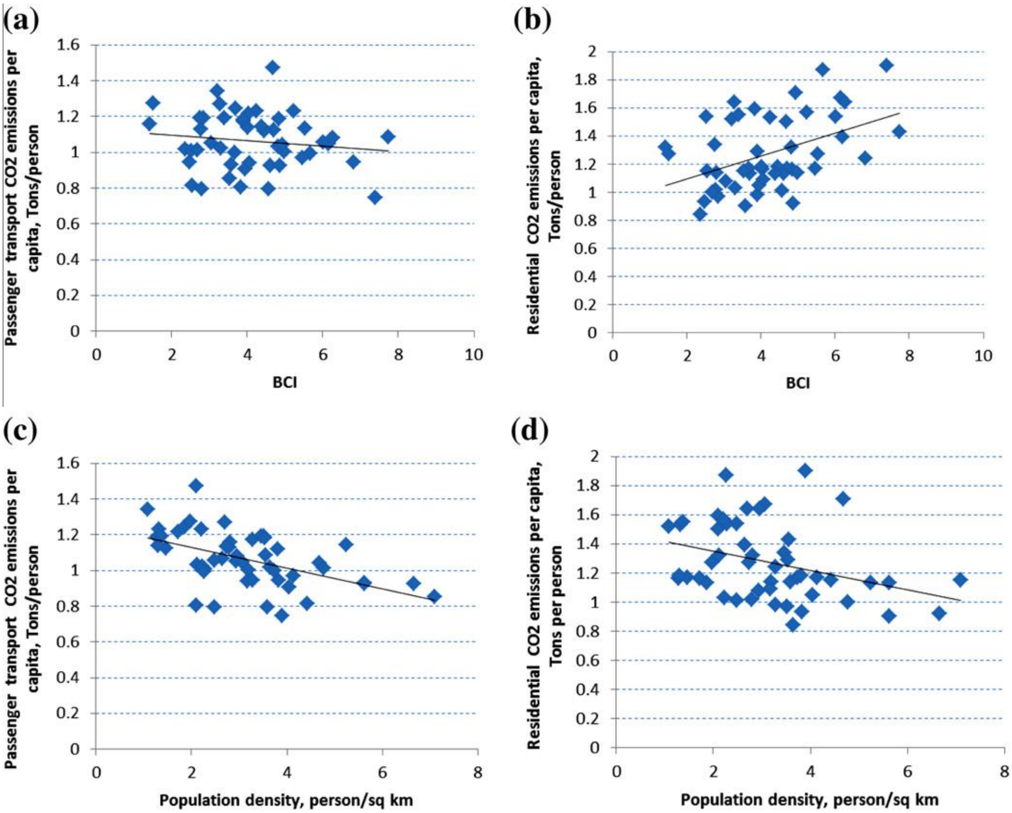

Fig. 3. Scatterplot of sectoral per capita CO2 emissions with population density and BCI.

density only shows the prevalence of high population concentration in a given area and cannot consider the patterns of settlement which has important bearing on transport and residential CO_2 emissions. Our analyses (Fig. 3) show that higher population density may be better for lower emissions in general sense but a better spatial organization of settlements within cities for this population can affect CO_2 substantially. As mentioned earlier and re-enforced in Fig.3, too denser and mono-centric urban settlement could increase residential emissions.

For the highest correlated sectors, i.e. residential and passenger transport, we carried out further regression analyses as shown in Table 5. However, we must remind readers that the key issues analyzed in this paper are correlations between the spatial variables of urban form (the metrics) with CO_2 emissions that are described above. For the residential sector, Income ($p < 0.01$) and AveTemp ($p < 0.001$) have negative effects on per capita CO_2 emissions, and Pop ($p < 0.05$) has a positive effect on per capita CO_2 emissions. This means that a higher average temperature, higher income and smaller city population size lead to the less CO_2 emissions per capita for the residential sector. Explaining the effect of the average temperature and income is difficult in our analyses and are subject to further exploration. Ideally, if data and time were available, we could have used the heating-degree-days and the cooling-degree-days instead of average temperature to reflect the geographical position of cities and to distinguish the relative importance of summer cooling and winter heating.

For the passenger transportation sector, AveTemp ($p < 0.001$) and BCI ($p < 0.01$) have negative effects on CO_2 emissions, and Urban ($p < 0.001$) has a positive effect on CO_2 emissions. This means that a higher average temperature, mono-centric dense settlement of city and less urban area per capita (high population density) lead to less CO_2 emissions per capita from the passenger transport sector.

Other than the average temperature, our results on the implications of population density and mono-centric dense settlement to CO_2 from the pass-transport sector support the commonly held view in the past literature. In our analyses, it was also interesting to see that residential CO_2 was responsive to income and city population size while the pass-transport CO_2 was responsive to mono-centricism and dense/sprawl of settlements and population density.

Landscape metrics approach to study CO_2 emission in urban area is not yet reported in order to compare the results of this study. Only one recent study used somewhat similar approach for energy use in Pearl River Delta in China (Chen et al., 2011) involving five big cities. It showed that the urban size, fragmentation of urban land use patterns, and irregularity of urban land use patterns are positively correlated with total energy consumption (not sectoral), while dominance of the largest urban patch is negatively correlated.

4. Conclusions

This study examined various methods to characterize urban forms and investigated the relationship between CO_2 emissions and urban form represented by spatial indices derived from satellite imagery and social economic variables in fifty Japanese cities of small and medium population. Our spatial indices to characterize urban form addressed the compactness and the complexity of urban settlements by considering shape, density, extent of irregularity and ruggedness of urban settlement patches, and the extent of centrality or mono-centricism and population density in cities.

Our analysis showed that the per capita CO_2 emissions from residential and passengers transport sectors of cities have significant correlations with the spatial variables of urban form, leaving out the commercial, industrial and freight transportation sectors. For the residential sector, less fragmented and more regular shaped urban settlement patches is correlated to lower residential per capita CO_2 emissions in cities, but too dense settlements in mono-centric form correlated to greater per capita CO_2 emissions. The latter finding points to the fact that compact settlements may not always be favorable for the residential sector. If this is true for larger samples, of which we are not sure, the possible reasons could be several e.g. too compact settlements can compromise with the flexibility of building design such as for sky lighting, natural ventilation and others. For the passenger transport sector, our findings endorse that less fragmented and more regular shaped settlement patches and denser settlements in mono-centric form lower the per capita CO_2 emissions of cities. Collectively, it means that a denser settlement may leads to lower CO_2 emissions from the residential and passenger transport sectors, but too dense urban settlements in mono-centric form may increase CO_2 emissions from the residential sector. Similarly, the effect of urban complexity on residential sector CO_2 emissions was not significant, while greater urban complexities may lead to a reduction of CO_2 in the passenger transport sector. However, the role of complexity is far less significant to both sectors.

In our analyses, we also found that the residential CO_2 emission per capita was negatively correlated to income and positively to city-size (in terms of population), while the pass-transport CO_2 per capita was positively correlated to the dense and mono-centric settlement form and population density.

These findings are useful in policy discussions to develop strategies for low carbon societies in small and medium scale cities in Japan since such efforts are underway at national, prefectural and city levels. Our results favor a high income, smaller population size, and denser city for lower CO_2 emissions. The facts that urban form is not meaningfully related to commercial, industrial or freight emissions but only slightly related to transport and residential emissions are a clear message to decision makers for a complicated relationship of urban form and overall CO_2 emissions deserving a detailed sectoral scrutiny. Our results also show to decision makers that urban policies aiming for a better urban form must go beyond population density in small and mid-size cities and serious considerations to and understanding of a better spatial organization of settlements by striking a balance between impacts of different settlements patterns to different sectors is prerequisite (for e.g. we found a combination of too dense and monocentric settlement might increase per capita residential CO_2 emissions). However, generalization of the finding in this paper needs to be done carefully and it may not always be applicable in other contexts. At the same time, a number of other spatial factors and non-

Appendix A

City name	Income	Pop	AveTemp	BCI	CI	AWMPFD	Urban	Indus CO_2	Comm CO_2	Resi CO_2	Trans CO_2	PassCar CO_2	FreiCar CO_2
	Thousand Yen/person	Number	°C	Index	Index	Index	Sq km/person	Ton of CO_2/person					
Akita	1240	333,109	11.7	6.26	0.0005	1.404	0.339	2.58	1.36	1.64	2.4244	1.0785	1.3401
Aomori	1124	311,508	10.1	7.39	0.001	1.405	0.257	2.78	1.33	1.9	1.7307	0.7478	0.9788
Chitose	1323	91,437	6.7	4.68	0.0012	1.423	0.478	2.1	1.07	1.5	2.3867	1.4708	0.7147
Ebetsu	1147	125,601	6.6	5.22	0.0009	1.417	0.451	2.77	0.63	1.57	1.9460	1.2294	0.6354
Fukuchi	1145	81,977	14.4	2.84	0.0014	1.326	0.284	4.48	1.23	0.97	2.1614	1.1922	0.9425
Fukui	1439	269,144	14.5	6.19	0.0006	1.393	0.378	3.21	1.57	1.39	2.1484	1.0639	1.0735
Fukushima	1279	290,869	12.9	5.53	0.0005	1.436	0.366	2.21	1.25	1.27	1.9357	1.1352	0.7813
Gotenba	1611	85,976	12.7	3.9	0.0014	1.385	0.304	2.82	1.29	0.98	1.9683	1.1712	0.7889
Hachinohe	1116	244,700	10.1	5.66	0.0005	1.403	0.442	3.11	1.2	1.87	2.2728	0.9953	1.2853
Hakusan	1368	109,450	14.8	2.76	0.0012	1.359	0.289	4.25	1.37	1.34	2.5940	1.1915	1.3718
Hanamaki	1009	105,028	10.2	4.24	0.0003	1.35	0.763	3.04	1.34	1.53	2.2499	1.2319	1.0056
Hikone	1387	109,779	14.8	3.94	0.0025	1.388	0.247	3.18	1.23	1.05	1.6064	0.9038	0.6547
Ichinoseki	942	125,818	11.3	3.39	0.0002	1.335	0.73	3.36	1.49	1.55	2.5434	1.1897	1.3464
Iida	1233	108,624	12.7	4.98	0.0018	1.431	0.314	4.2	1.29	1.14	1.9053	1.0015	0.8983
Iwaki	1109	354,492	13.2	1.51	0.0002	1.437	0.509	3.22	1.02	1.27	2.1832	1.2745	0.9001
Iwamizawa	1043	93,677	7.5	3.27	0.001	1.39	0.371	2.9	0.95	1.64	2.0930	1.2677	0.7667
Iwata	1517	170,899	15.8	2.67	0.0009	1.408	0.21	2.81	0.9	1	2.0227	1.0104	0.9984
Joetsu	1247	208,082	13.5	4.01	0.0003	1.43	0.768	3.8	1.35	1.18	2.5629	1.1364	1.4105
Kameoka	1228	93,996	15.9	2.48	0.0016	1.386	0.261	3.13	0.82	0.93	1.4788	0.9464	0.4990
Kanazawa	1524	454,607	14.8	7.74	0.0012	1.43	0.281	3.34	1.73	1.43	2.0898	1.0845	0.9932
Kanoya	941	106,208	17.5	3.29	0.0005	1.336	0.449	2.89	0.92	1.03	1.9515	1.0205	0.8500
Kirishima	1007	127,309	15.1	2.77	0.0006	1.399	0.359	2.47	1.01	1.02	1.7666	1.1308	0.6161
Kitakami	1161	94,321	10.8	3.84	0.0007	1.341	0.475	3.1	1.17	1.59	2.5912	0.8038	1.7884
Koriyama	1229	338,834	12.1	6.82	0.0005	1.372	0.305	2.94	1.22	1.24	2.0406	0.9435	1.0860
Kurume	1201	306,434	16.5	3.52	0.0008	1.426	0.141	2.58	1.06	1.15	1.5877	0.8514	0.7060
Miyako	915	170,955	16.5	4.71	0.0003	1.412	0.685	3.08	0.94	1.17	2.7149	1.1215	1.7523

Morioka	1362	300,746	10	6.14	0.0005	1.403	0.326	2.56	1.54	1.67	1.8108	1.0453	0.7543
Nagahama	1341	82,676	14.8	4.57	0.0018	1.407	0.402	3.67	1.24	1.01	1.8015	0.7968	0.9955
Nagano	1370	378,512	11.6	5.47	0.0008	1.429	0.242	3.98	1.37	1.17	1.9147	0.9697	0.9342
Nagaoka	1150	283,224	12.9	4.45	0.0004	1.362	0.263	2.98	1.27	1.18	2.2737	1.1206	1.1513
Nobeoka	925	135,182	16.7	2.79	0.0009	1.407	0.278	3.57	1.64	1.14	1.3594	0.7922	0.5515
Oita	1249	462,317	16.8	4.38	0.0006	1.428	0.191	3.44	1.08	1.13	1.9566	1.1410	0.7817
Okazaki	1728	363,807	15.3	4.86	0.0012	1.478	0.15	3.28	0.98	0.92	1.4980	0.9254	0.5356
Omura	1105	88,040	16.9	3.57	0.0034	1.464	0.178	2.16	1.94	0.9	3.0013	0.9307	2.0624
Osaki	1011	138,491	10.8	4.03	0.0003	1.34	0.581	3.49	0.96	1.16	2.3491	1.2158	1.1209
Otaru	1013	142,161	8.4	4.94	0.0035	1.438	0.214	2.42	1.24	1.71	2.1870	1.0426	1.0942
Saga	1181	241,361	16.6	4.62	0.001	1.421	0.178	3.02	1.16	1.13	1.7461	0.9235	0.7972
Sakai	1318	92,318	14.5	1.41	0.0011	1.336	0.357	3.14	1.25	1.32	2.3055	1.1590	1.1494
Shibata	1091	104,634	13.4	4.84	0.0007	1.382	0.783	3.7	1.13	1.16	2.0812	1.1864	0.8775
Takayama	1281	96,231	11	3.69	0.0005	1.341	0.537	4.89	2.32	1.13	2.3478	1.2464	1.0959
Tottori	1193	201,740	14.9	4.06	0.0006	1.393	0.315	2.9	1.24	1.09	1.6841	0.9398	0.7371
Toyama	1420	421,239	14.2	6.02	0.0005	1.455	0.402	4.15	1.5	1.54	2.0038	1.0562	0.9278
Toyooka	960	89,208	14.5	2.37	0.0011	1.312	0.274	4.45	1.69	0.84	1.8079	1.0180	0.7794
Tsuruoka	997	142,384	12.1	3.89	0.0008	1.365	0.283	4.11	1.27	1.29	2.0460	1.1811	0.8640
Tsuyama	1111	110,569	13.9	3.05	0.0007	1.377	0.34	3.6	1.28	1.08	1.9503	1.0527	0.8996
Ueda	1232	163,651	11.6	3.66	0.001	1.429	0.268	3.23	1.3	1.17	1.6767	1.0001	0.6639
Uwajima	886	89,444	16.6	2.55	0.0014	1.34	0.226	4.5	3.96	1.15	2.4343	0.8131	1.6041
Yokote	863	103,652	10.9	2.51	0.0006	1.34	0.438	3.21	1.17	1.54	2.2235	1.0082	1.2169
Yonezawa	1099	93,178	11.4	4.81	0.0009	1.4	0.472	3.12	1.29	1.32	2.0758	1.0310	1.0385
Yurihonjo	966	89,555	11.9	3.21	0.0003	1.32	0.916	3.84	1.04	1.52	2.1166	1.3395	0.7655

spatial factors may be more influential. In this study, we limited the size of our study area to smaller to medium sized cities to allow for an examination of cities with similar conditions. For future study, one needs to include other sizes of cities in Japan, and possibly also extend it to cities outside Japan for generalizing the findings. Although five urban form indices showed correlations to CO_2 emissions, the correlations are yet not very strong. We need to investigate more indices that more strongly characterize urban forms. Also, we calculated landscape matrices at the 30 m resolution, we did not carry out analyses at different resolutions and the results may be sensitive to the resolution of the classified images.

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Appendix A

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