IDENTIFYING PREVALENT LANDCOVER CONVERSION PATTERNS IN REGIONS OF DIFFERENT MAJOR DEVELOPMENTS

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1. INTRODUCTION

Urbanization is a process of transforming natural, such as wetlands and forests, or agricultural landscapes to built environments which typically contain large amounts of impervious surfaces. Changes in landcover types are a direct consequence of urbanization. As the process of urbanization evolves, landcover pattern, namely the types of landcover and their proportions, present in a city and its proximity may also vary over time. Landcover pattern is an integrated reflection of the available natural resources, dynamic natural processes, and anthropogenic activities in a region. Many studies have found that changes in landcover pattern can have significant impact on urban ecosystems. Cheng et al. (2008) assessed the effect of landcover changes in urban fringe on ambient air temperature using remote sensing images. It was concluded that losses of paddy field to urban built-up would result in ambient air temperature rise.

Not only are landcover changes the most apparent effect of urbanization, but also the driving forces of many ecological consequences of urbanization. Thus, characterizing the landcover pattern in a region is crucial for assessing the effects of urbanization. Quantitative analysis of landcover pattern is generally accomplished by using landscape metrics which, in recent years, are often derived from remote sensing images. Landscape metrics are useful in describing landuse structure and detecting landuse changes. Another important aspect of landcover pattern analysis is the spatial and temporal variation of these landscape metrics. Through a transect gradient analysis of landscape metrics, Luck and Wu (2002) demonstrated that the spatial pattern of urbanization could be reliably quantified and the location of the urbanization center could be identified precisely and consistently with multiple landscape metrics.

Although landscape metrics have been widely applied to characterizing landcover patterns and detecting spatial and temporal changes in landcover patterns, there have been relatively few studies on the feasibility of quantitatively comparing landcover patterns and degrees of urbanization in different major cities using a set of common landscape metrics. Thus, this study aims to explore the feasibility of characterizing landcover patterns using landscape metrics and other indices derived from remote sensing images and, via these common indicators, to compare landcover patterns in cities of different degrees of urbanization. Specifically, we seek to develop an index which can provide a quantitative representation of the degree of urbanization for different cities.

2. STUDY AREAS AND DATA

Three regions (Tokyo and Kyoto in Japan and Taipei in Taiwan) of different degrees of urbanization were chosen for this study. The area and degree of urbanization of these regions are described in Table 1.

ALOS satellite multispectral images of these studies areas were collected. These images were acquired by the AVNIR2 sensor onboard the ALOS satellite with a spatial resolution of 10 m x 10 m. AVNIR2 sensor acquires images in four spectral bands – blue (B, 0.42 – 0.50 μm), green (G, 0.52 – 0.60 μm), red (R, 0.61 – 0.69 μm), and near infrared (IR, 0.76 – 0.89 μm). Image acquisition dates of individual study areas are also shown in Table 1. All these satellite images were preprocessed for radiometric and geometric corrections by the Japan Aerospace Exploration Agency (JAXA). Thus, all images were georeferenced to map projection coordinates.

Table 1. Three study areas with different degrees of urbanization.

Study area	Area size	ALOS scene acquisition dates
Tokyo	15 km x 15 km	21/11/2006
Kyoto	15 km x 15 km	09/10/2006
Taipei	15 km x 15 km	05/04/2008

3. LANDUSE/LANDCOVER CLASSIFICATION

Prior to landcover pattern analysis, landuse/landcover (LULC) classification needs to be conducted for each study area. In this study an indicator kriging approach for LULC classification was adopted. The indicator kriging (IK) classification is a nonparametric supervised classification approach that can achieve high classification accuracy for training data set. A brief description of the IK approach for LULC classification is given in the Hung et al. (2010). In this study, four landcover classes, including woods, grass/crop, built-up and water bodies, were adopted for LULC classification. Among these landcover types, woods represents land surface covered by forest, trees, and shrubs. Grass/crop includes areas covered by grass, paddy field, and vegetable crops. Built-up landcover includes buildings, paved surface, and bare soil. For supervised classification, digital numbers (or grey levels) of the red and near infrared ALOS spectral bands were chosen as classification features. Classification results are evaluated based on their training-pixels-based confusion matrices. Under most circumstances, our LULC classification yields higher than 95% classification accuracies (including the producer's, user's and overall accuracies). Area percentage of individual landcover types in the three study areas are shown in Table 2. Tokyo study area has a dominant area percentage of built-up coverage, whereas Kyoto has a more balanced built-up and vegetation (including woods and grass/crop) coverage. Comparing to Tokyo, Taipei has a less dominant percentage of built-up coverage and a significantly higher percentage of vegetation coverage. In a rough sense, among these three cities, Tokyo has the highest degree of urbanization and Kyoto has the least degree, with Taipei ranked in the middle. Figure 1 demonstrates landcover images, based on the results of LULC classification, of the three study areas.

Table 2. Area percentage of individual landcover types in different study areas.

Landcover type	Areal percentage (%) Tokyo	Kyoto	Taipei
Woods	7.7	33.9	18.9
Grass/Crop	5.7	11.5	11.5
Built-up	85.8	53.4	63.6
Water	0.8	1.2	6.0

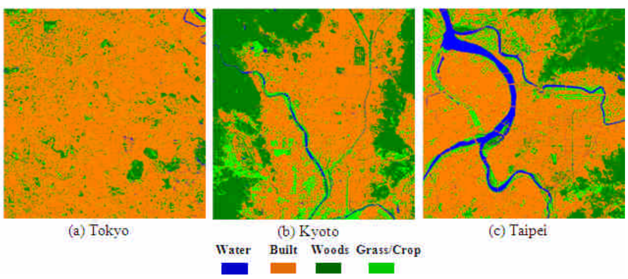


Fig.1 Landcover images of the three study areas.

4. LANDCOVER PATTERNS IN COVERAGE-RATIO SPACE

Cheng et al. (2008) studied the effect of different landcover changes on ambient air temperature. A scatter plot of cells in coverage-ratio space was used to characterize landcover condition of the study area. The same concept was adopted in this study to demonstrate and compare the landcover patterns of different study areas.

A cell is defined as an area having a spatial coverage of 1 km x 1 km. each cell is associated with four area percentages (i.e. coverage ratios) corresponding to landcover types of woods, crop/grass, built-up, and water bodies. Since water bodies account for very small and least coverage in most cells in our study areas, scatter plot of cells in a coverage-ratio space formed by the other three landcover types (see Figure 2) will be discussed.

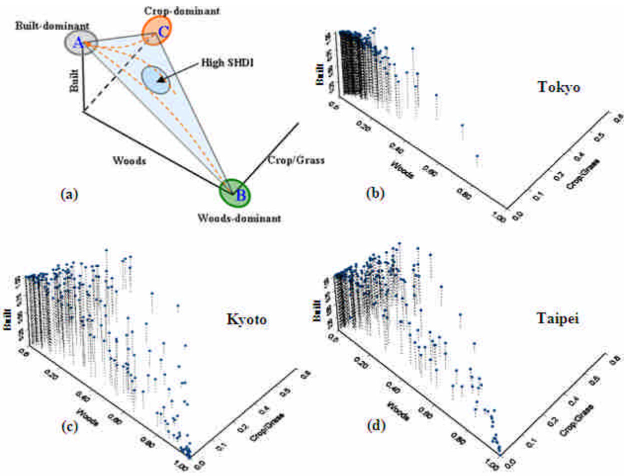


Fig. 2 Landcover pattern in coverage-ratio space. (a) Schematic illustration showing regions of different dominant landcover types. (b) – (d) Existing landcover patterns in the Tokyo, Kyoto, and Taipei study areas, respectively. (Source: Hung et al., 2010)

Figure 2(a) demonstrates that, neglecting the coverage ratio of water bodies, all cells should fall on a plane (hereafter referred to as the *coverage-ratio plane*) defined by three vertices (points A, B, and C) of dominant landcover types. Urbanization can be viewed as a process of cells on the coverage-ratio plane merging from points B (woods dominant) and C (crop/grass dominant) towards the confluence point A (built-up dominant). Thus, it can be seen clearly from Fig. 2 that Tokyo study area is most urbanized with very low coverage ratio of woods or grass/crop landcover type. The Taipei study area has majority of its cells concentrated near built-dominant point A, although there are also many cells falling along a curved path near the AB line (Fig. 2(d)). Comparing to the Tokyo and Taipei study areas, concentration of cells near built-dominant point A is less significant for the Kyoto study area. Cells are more widely spread over the coverage-ratio plane, indicating a good mixture of different landcover types within the Kyoto study area. It also indicates that the Kyoto study area is least urbanized among the three study areas.

5. NDVI-BASED LANDCOVER PATTERN ANALYSIS

Urbanization is characterized by the transformation of landcover from natural landscapes, such as forests and wetlands, and agricultural landuse, to built environments which typically contain large amounts of impervious surfaces such as concrete, asphalt and roofs. A simple index which has been widely used in remote sensing applications for differentiating forests, agricultural landcover, and built environment is the normalized difference vegetation index (NDVI) defined as follows:

$$NDVI = \frac{IR - R}{IR + R} \qquad (1)$$

where IR and R respectively represent digital number (DN) or radiance (L) of the near infrared and red spectral bands.

In this study minimum digital numbers of individual bands were subtracted from the raw DNs, and then the adjusted DNs were converted to radiances. Subtraction of the minimum DNs helps to alleviate the effect of atmospheric scattering (Chavez, 1975; Schott, 1997). NDVI values of individual pixels were calculated using radiances of the red and near infrared bands, i.e.

$$NDVI_{pixel} = \frac{(L_{IR} - L_{IR,\min}) - (L_R - L_{R,\min})}{(L_{IR} - L_{IR,\min}) + (L_R - L_{R,\min})} \qquad (2)$$

Finally, cell-average NDVI ($NDVI_{cell}$) was calculated for individual cells of the three study areas.

Figure 3 shows the empirical probability density function (ECDF) of $NDVI_{pixel}$ of different landcover types in the three study areas. In general, NDVI values of the same landcover type in three study areas vary in the same range, except the landcover type of water. It also demonstrates that most built-up pixels have negative NDVI values, whereas most grass/crop pixels and almost all woods pixels have positive NDVI values. In particular, pixels of woods landcover type have the highest NDVI.

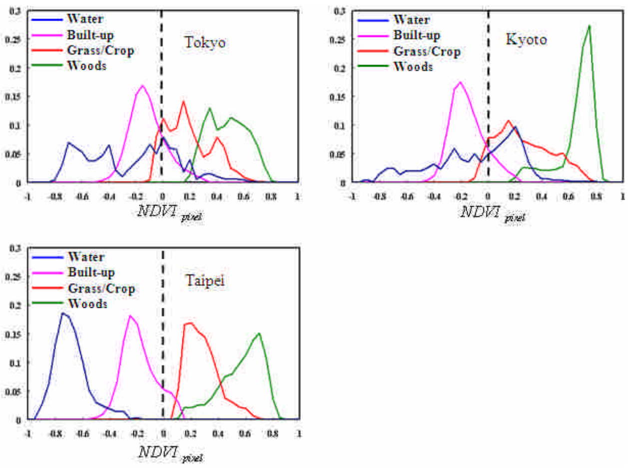


Fig. 3 ECDF of landcover-specific NDVI in different study areas. (Source: Hung et al., 2010)

As a result, cells with dominant built-up landcover tend to have negative cell-average NDVI, and in contrast, cells with dominant grass/crop or woods landcover type are associated with positive NDVI values. The higher percentage of woods landcover a cell has, the higher its cell-average NDVI. Thus, cell-average NDVI can serve as a quantitative indicator of the effect of urbanization and its variation within the study area can reveal areas of different degrees of urbanization.

Excluding a few cells with higher coverage ratio of water in the Taipei study area, cell-average NDVI ($NDVI_{cell}$) alone can be used as an indicator for identifying cells of built-up dominant, woods dominant, and diversified landcover. The following criteria can then be adopted for delineation of areas with different dominant landcover types:

$$NDVI_{cell} < 0, \quad \text{built-up dominant} \qquad (3a)$$

$$0 \le NDVI_{cell} < 0.4, \quad \text{diversified landcover} \qquad (3b)$$

$$0.4 \le NDVI_{cell}, \quad \text{woods dominant} \qquad (3c)$$

Implementation of such $NDVI_{cell}$ – based method of dominant-landcover-areas delineation does not require an a priori LULC classification, and thus is particularly useful when good training data for LULC classification are not available. Using $NDVI_{cell}$ and the criteria of Eqs. (3a)-(3c), areas of different dominant landcover types and areas with more diversified landcover pattern of the three study areas were delineated and shown in Figure 4.

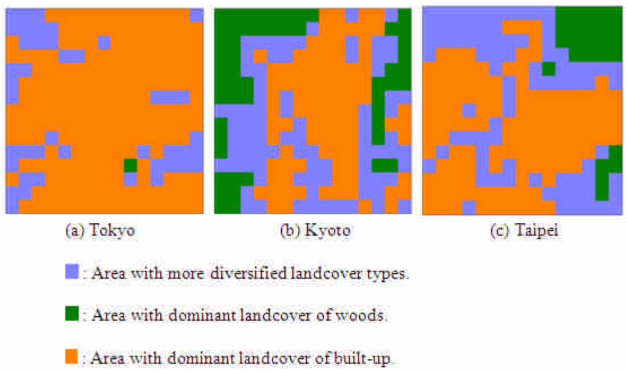


Fig. 4 Areas of different dominant landcover types in the three study areas delineated using cell-average NDVI. (Source: Hung et al., 2010)

The Tokyo study area has the highest proportion of built-up dominated area, while Kyoto has the least. The areas with more diversified landcover seem to be located between areas with dominant landcover of built-up and woods, and maybe viewed as transition areas. The spatial pattern of different dominant landcover types in Figure 4 differentiates built-dominant and woods-dominant areas, affirming the feasibility of dominant landcover delineation using the cell-average NDVI alone.

6. Assessing the degree of urbanization using an urbanization index

The cell distribution in the coverage-ratio space can only serve as a visually and qualitative indicator of the degree of urbanization. An urbanization index (UI) which not only reflects the characteristics of urbanization, but also provides a comparable scale is worth pursuing.

The most apparent effect of urbanization is the increase of built-up landcover. As the process of urbanization continues, the built-up dominant areas expand and the coverage ratio of built-up landcover type increases. However, modern urban planning and zoning may also require establishing urban forestry or city parks and planting of road trees to alleviate the adverse effect of urbanization. Presence of trees, parks, and forestry in a neighborhood can be reflected by higher cell-average NDVI values.

There exist a few definitions of urbanization index in the literature, including the ratio of apartment houses in total construction housing (Kouichi, 1987), road density and percentage of built area (Lee et al., 2004), and the ratio of building coverage per unit area (Chen, 2007). These indices basically use the percentage of built area to quantify the degree of urbanization, and fail to consider the effect of vegetation cover. Thus, we propose to develop a cell-specific urbanization index by integrating the coverage-ratio of built-up landcover type and the cell-average NDVI:

$$UI_{cell} = p_b \cdot (1 - NDVI_{cell}) \tag{4}$$

where p_b represents the coverage-ratio of built-up landcover type of individual cells. Theoretically, the value of cell-specific urbanization index can vary between 0 and 2 since $-1 \le NDVI_{cell} \le 1$. In reality, most UI_{cell} values fall in between 0 and 1, and higher UI_{cell} values indicate more significant effect of urbanization. Figure 5 demonstrates the $UI_{cell} \sim p_b$ relationship of the three study areas.

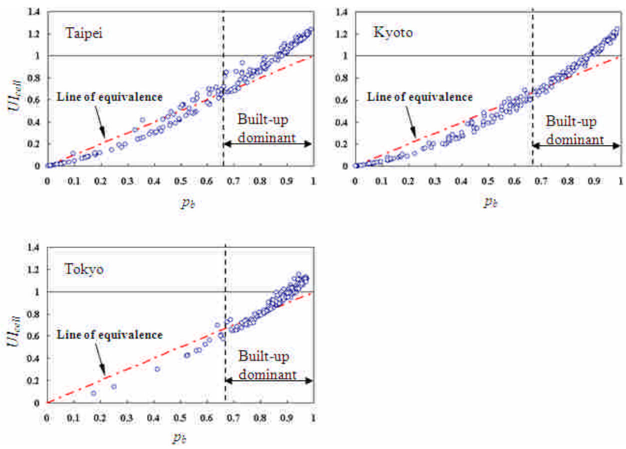


Fig. 5 Relationship between cell-specific urbanization index (UI_{cell}) and coverage-ratio of built-up landcover type (p_b). (Source: Hung et al., 2010)

It is interesting to observe that most of built-up dominant cells fall above the line-of-equivalence, whereas most non-built-up-dominant cells fall below the line-of-equivalence. Such scattering reflects the contribution of cell-average NDVI to lower the urbanization index and the adverse effect (higher urbanization index) due to high built-up coverage ratio. The line-of-equivalence represents the case of using the built-up coverage alone as the urbanization index.

For an overall comparison of the degrees of urbanization of the three study areas, average urbanization index $\overline{UI}$ for each study area was calculated. Value of $\overline{UI}$ for the Tokyo, Kyoto, and Taipei study areas are 0.91, 0.55, and 0.72, respectively. These values are consistent with the qualitative evaluation of the degree of urbanization as described in section 4.

Although quantitatively applicable, utilization of the proposed urbanization index should be exercised with care. UI_{cell} is dependent on cell-average NDVI which may change with season due to growth condition of the vegetation. Thus, it is recommended to calculate UI_{cell} and $\overline{UI}$ using remote sensing images which can appropriately reflect the vegetation cover (for example, images acquired in summer) of the study area.

7. Gradient analysis of landscape spatial pattern using cell-specific urbanization index

As has been demonstrated by Luck and Wu (2002) and Weng (2007), gradient analysis of landscape metrics can be applied to show the spatial variation of landcover pattern. Since UI_{cell} is calculated for individual cells, it is a convenient choice for urban landscape gradient analysis. We demonstrate such practice by showing changes of UI_{cell} along three west-to-east transects in the Kyoto study area (see Figure 6). Variation of landscape metrics along the three transects correctly reflects the influence of mountains on the west and east sides and the river (Katsuragawa) flowing from northwest corner towards the lower center of the Kyoto city.

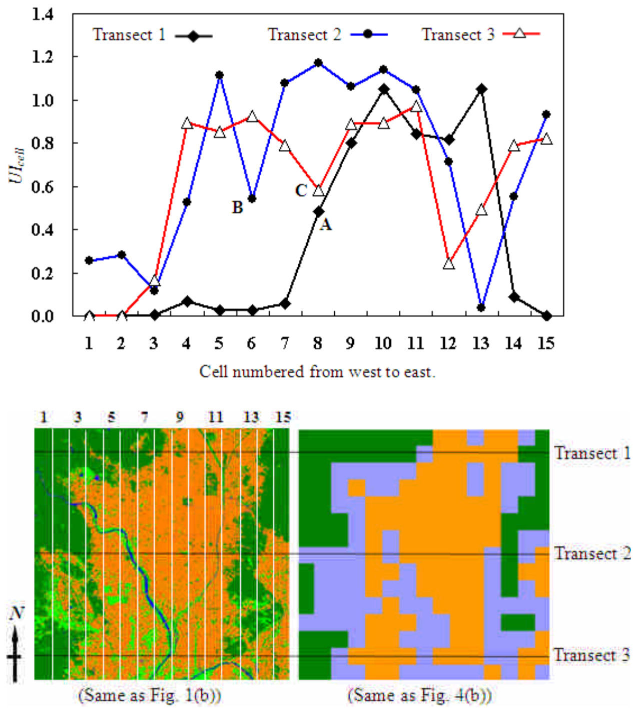


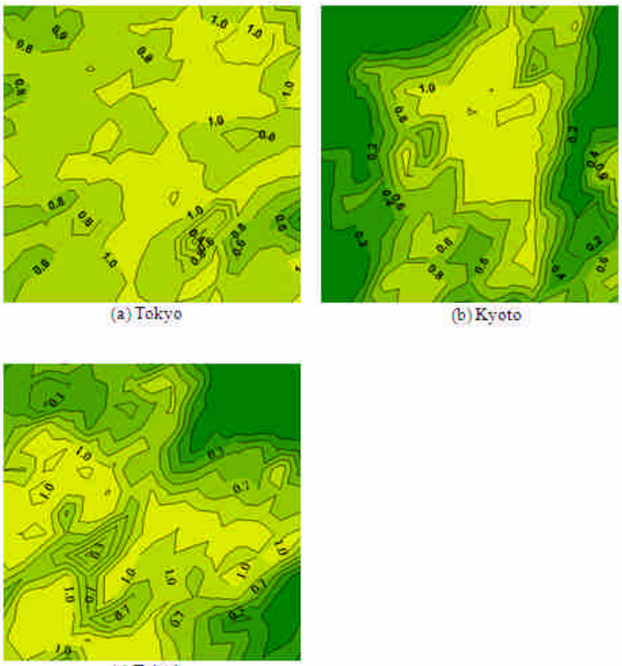
Fig. 6 Transect gradient analysis of the cell-specific urbanization index of the Kyoto study area. (Source: Hung et al., 2010)

The rationale of incorporating $NDVI_{cell}$ in Eq. (4) is that coverage ratio of built-up landcover type alone cannot appropriately represent the degree of urbanization. Two cells having the same or similar coverage ratios of built-up landcover type may have significantly different values of UI_{cell} due to their differences in coverage ratios of woods and grass/crop landcover types. Such $NDVI_{cell}$ influence can be exemplified by coverage ratios of different landcover types associated to points A, B, and C in Figure 6 (see data in Table 3). Point A of transect 1 has a higher built-up coverage ratio than point B of transect 2, whereas point B is associated with a higher urbanization index. In addition, point A and C have similar built-up coverage ratios while point C is associated with a significantly higher value of UI_{cell} than point A. In particular, the difference in UI_{cell} values of point A and C demonstrates higher contribution to urbanization index by the grass/crop landcover, as compared to woods landcover, due to its more intense anthropogenic activities than the woods landcover type.

Table 3. Coverage ratios of different landcover types for points A, B, and C in Figure 6.

	Landcover type				
	Built-up	Woods	Grass/Crop	Water	UI_{cell}
A	0.582	0.358	0.054	0.006	0.486
B	0.551	0.130	0.214	0.105	0.540
C	0.595	0.049	0.312	0.044	0.581

Variation of cell-specific urbanization index can also be displayed in a two-dimensional space to explore the city center and areas with higher degrees of urbanization. Figure 7 demonstrates UI_{cell} contour maps of the three study areas. The Tokyo study area has higher than 0.8 UI_{cell} values over most of its coverage, and is clearly most urbanized among the three study areas. Taking $UI_{cell} \geq 1.0$ as a criterion, the most urbanized district in each of the three study areas can be identified. For the Kyoto study area, the most urbanized district falls within an area restricted between two rivers (the Kamogawa and Katsuragawa) flowing through the city. In contrast, the Taipei study area is dissected by the Damsui River and three most urbanized districts can be identified. As for the Tokyo study area, the most urbanized district is located in the surrounding of the Tokyo Metropolitan Office, including several busiest wards in Tokyo. Generally speaking, these identified most urbanized districts are in agreement with areas of highest population density of the three study areas, indicating the capability of UI_{cell} as a measure of the degree of urbanization. Such gradient analysis can also be conducted for the same study area over different time periods to reveal the spatiotemporal trend of urbanization. It is also worthy to note that, since the proposed cell-specific urbanization index integrates the effects of built-up coverage and NDVI, there exists a potential for study of urban heat island using the proposed urbanization index.



(a) Tokyo (b) Kyoto (c) Taipei

Fig. 7 Two-dimensional gradient analysis of the cell-specific urbanization index of the Tokyo, Kyoto, and Taipei study areas. (Source: Hung et al., 2010)

As a final remark of this study, we emphasize that, like many other similar studies, the results of our landcover pattern analyses are dependent on the extent of study areas chosen for this study. While the Tokyo study area only encompasses a subregion within the full juridical extent of the Tokyo Metropolis, the average urbanization index $\overline{UI}$ may vary if the whole Tokyo Metropolis were chosen as the study area.

8. Conclusions

In this study we demonstrate the feasibility of identifying and comparing landcover patterns in three study areas, namely Tokyo, Kyoto, and Taipei, of different degrees of urbanization, using ALOS multispectral images. Landcover patterns were characterized by three key aspects: (1) number of different landcover types, (2) relative proportions of landcover types, and (3) spatial distribution of these landcover types. Landcover patterns in different study areas were compared, with respect to these aspects, through three approaches including distribution of cells in landcover coverage-ratio space and a dominant landcover delineation method using cell-average NDVI. An urbanization index which can be used as a measure of degree of urbanization is also developed by integrating the coverage-ratio of built-up landcover type and the cell-average NDVI. A few concluding remarks are drawn as follows:

(1) Comparing to the Tokyo and Taipei study areas, Kyoto is least urbanized and enjoys a good mixture of different landcover types, based on the analysis of landcover pattern in coverage-ratio space.

(2) Cell-average NDVI alone can be used as an indicator for delineation of dominant landcover areas. Implementation of such $NDVI_{cell}$ – based method does not require an a priori LULC classification, and thus is particularly useful when good training data for LULC classification are not available.

(3) Area-average urbanization index for the Tokyo, Kyoto, and Taipei study areas are 0.91, 0.55, and 0.72, respectively. The cell-specific urbanization index can also be used for transect and two-dimensional gradient analyses to show the spatial variation of the degree of urbanization within each study area.

9. ACKNOWLEDGEMENTS

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10. REFERENCES

[1] Chavez, P.S., 1975. Atmospheric, Solar, and M.T.F. Corrections for ERTS Digital Imagery. Proceedings, American Society of Photogrammetry, 69-69a.

[2] Chen, L., 2007. Land use/cover change and environmental effects. 2007-USA-AZU Bilateral Workshop. Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences. http://www.asu.edu/chinainitiatives/Workshop_2/2007_USA-AZU_ChenLiding.pdf.

[3] Cheng, K.S., Su, Y.F., Kuo, F.T., Hung, W.C., Chiang, J.L., 2008. Assessing the effect of landcover on air temperature using remote sensing images - A pilot study in northern Taiwan. Landscape and Urban Planning, 85(2), 85-96.

[4] Hung, W.C., Chen, Y.C., Cheng, K.S., 2010. Comparing landcover patterns in Tokyo, Kyoto, and Taipei using ALOS multispectral images. Landscape and Urban Planning, 97: 132-145.

[5] Kouichi, I., 1987. Study on the estimation method of residential land use index in Tokyo metropolitan area. Journal of architecture, planning and environmental engineering, Transactions of Architectural Institute of Japan, 375, 114-125 (in Japanese).

[6] Lee, P., Ding, T., Hsu, F., Geng, S., 2004. Breeding bird species richness in Taiwan: distribution on gradients of elevation, primary productivity and urbanization. Journal of Biogeography, 31, 307–314.

[7] Luck, M., Wu, J., 2002. A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan region, Arizona, USA. Landscape Ecology, 17, 327–339.

[8] Schott, J.R., 1997. Remote Sensing – The Image Chain Approach, Oxford University Press.

[9] Weng, Y.C., 2007. Spatiotemporal changes of landscape pattern in response to urbanization. Landscape and Urban Planning, 81, 341–353.