ASSESSMENT OF ECOSYSTEM CLASSIFICATION SYSTEMS AT VARIOUS SCALES ON ENVIRONMENTAL PARAMETERS USING REMOTE SENSING TECHNIQUES

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ABSTRACT:

The main purpose of this study was to assess the effect of ecosystem classification systems at various scales on environmental parameters using remote sensing techniques. The processes included applying hybrid classification to generate a land-use map of northern Taiwan using Landsat-5 image in 1995; using the DTM and the SEBAL model to calculate 16 environmental parameters to compare the differences among various land-use types; and assessing the effects of 2 ecosystem classification (i.e., geographic climate method and watershed division method) on environmental parameters using stepwise discriminated analysis. The result indicated that the study area was classified into 7 land-use types (i.e., forest-land, building, farm-land, baring farm-land, water body, cloud, and shadow). Comparison of environmental parameters among different land-use types showed that forestland had higher value with cosine of solar incidence angle, twenty-four hour extraterrestrial radiation, net radiation, normalized difference vegetation index, emissivity, estimating friction velocity, surface roughness for momentum transport, sensible heat flux, soil heat flux, evapotranspiration, and had lower value with transmittance, air density, surface albedo, surface albedo at the top of atmosphere, aerodynamic resistance to heat transport, surface temperature. As for the assessment of ecosystem classification systems at various scales on environmental parameters, the result showed that ecosystem classification systems at various scales do cause the variation of environmental parameters according to the selected parameters and the number of parameters for discriminating land-use types. However, among environmental parameters, normalized difference vegetation index and emissivity are the most important factors regardless of ecosystem classification systems at various scales.

1. INTRODUCTION

Human activities for urbanization not only change the nature land cover, but also disturb the operations of ecosystem, and lead to the occurrence of global environment change. Therefore, considerable attention has been given for monitoring changes in the global environment recently (Andrew et al, 2005). To achieve the objective of monitoring global environment change, the acquisition of environmental large-scale information becomes the most important topic. As for acquiring global information, remote sensing has been proven a useful technique because it can easily and timely provide large-scale spatial and temporal ground information to study global environment change (Chen et al., 2006). In addition, satellite images can be used to extract the useful environmental parameters such as surface temperature, evapotranspiration etc. Due to these advantages, the combination of remote sensing and environmental parameters has been applied to analyze the impact of human disturbance on ecosystems for further studies of global environment change (Laymon et al., 1998; Menenti and Choudhury, 1993; Morse et al., 2000).

However, ecosystems are nested and resided within each other. The boundaries of ecosystems are open to transfer of energy and materials to or from other ecosystems. Because of the linkage among systems, energy exchange with its surroundings occurs at various spatial scales. Besides, a disturbance to a large system may also affect smaller component systems existed within it. Consequently, the relationship between an ecosystem at one scale and ecosystems at smaller or larger scales must be examined to predict human disturbance effect (Robert, 1996). Nevertheless, most of previous researches focused on the effect of global and regional scales on environmental parameters (Rao, 1990; Tokumaru and Kogan, 1993). Few studies pay attention to landscape or ecosystem scales and their effects on environmental parameters. For this reason, this study focuses on the application of remote sensing techniques to derive environmental parameters, particularly on assessing the effect of ecosystem classification systems at various scales on environmental parameters.

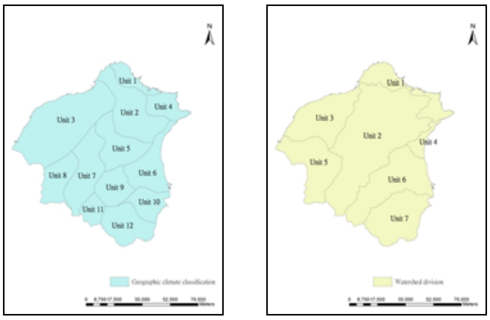
2. MATERIALS AND METHODS

2.1 Study Area and Materials

The study area (Figure 1) locates at northern Taiwan, which covers 734589.7ha and includes 5 counties (Kee-Lung, I-Lan, Taipei, Tao-Yuan, and Hsin-Chu).

To assess the effect of ecosystem classification systems at various scales on environmental parameters, two methods of ecosystem classification were used in this study. One is called the geographic climate method which is based on the controlling factor (i.e., climate) to classify land as ecosystems. The other is called the watershed division method which is regarded watershed units as ecosystems. Under various scales of each classification system, the study area is further classified into different numbers of ecosystems, for example, geographic climate method and watershed division method have 12 and 7 ecosystems, respectively (Figure. 2). There are several industrial or scientific campuses in the study area, which demand more water resource and may indirectly influence the operations of ecosystem. Therefore it is important to understand how land-use types and spatial classification systems affect the environmental parameters before making management decisions.

Figure 1. Location of the study area



a b

Figure 2. Spatial scales of 2 ecosystem classification systems (a: geographic climate method; b: watershed division method)

The materials in this study include the Landsat-5 TM image in 1995 and the digital terrain model (DTM) shown as Figure 3. Landsat-5 TM image contains 7 spectral bands from the visible band to the middle near-infrared (mid-IR) band. Band 1~ band 3 are the blue, green, and red bands; band 4 is the near IR; band 5 and band 7 are the mid-IR. Each of above 6 bands has a 30m ground resolution. Band 6 is the thermal IR with a 120m ground resolution. The study area was clipped to generate a land-use map after image radiometric and geometric corrections. As for the DTM with 40m resolution, it was provided by the Aerial Survey Institute of Forestry Bureau. Those two data were used to calculate environmental parameters of the study area.

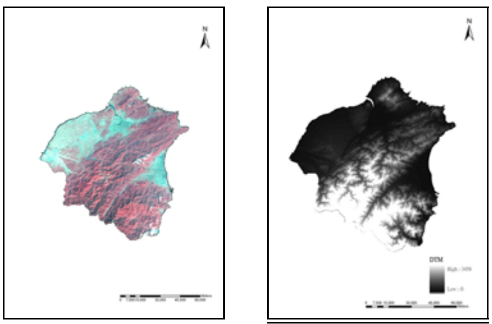


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Figure 3. Study materials (a: Landsat-5 TM image; b: DTM)

2.2 Methods

2.2.1 Land-use Classification using Hybrid Method:

The analytical procedures included 2 parts. Firstly, a land-use map of the study area was generated by hybrid image classification. Hybrid image classification integrates the supervised and unsupervised process to improve the classification accuracy (Lillesand & Kiefer, 2000). As for the processing procedure, several blocks were firstly selected from the Landsat image according to ground land-use information. Each block contained at least 3 to 4 kinds of land-use types. The selected blocks were clustered into spectral subclasses by unsupervised classification and then merged or deleted subclass signatures as appropriate based on transformed divergence (TD) as equation (1). In this study, TD was ranged from 0 to 2000. If 2 classes can be discriminated easily, then TD approaches 2000. After that, spectral signatures obtained from the selected blocks were pooled into a single spectral file. Finally, supervised classification method was applied to generate the land-use map of the study area according to the single spectral signatures.

$$
\begin{aligned}
TD &= 2000\left[1-\exp(-D/8)\right] \\
D &= \frac{1}{2}tr\left(\Sigma_i-\Sigma_j\right)\left(\Sigma_i^{-1}-\Sigma_j^{-1}\right)+ \\
&\frac{1}{2}tr\left[\left(\Sigma_i^{-1}-\Sigma_j^{-1}\right)\left(m_i-m_j\right)\left(m_i-m_j\right)^T\right]
\end{aligned}
\quad (1)
$$

where TD = transformed divergence
D = divergence
Σ_i = covariance matrix of class i
m_i= mean vector of class i
$tr[A]$ = sum of the diagonal line on matrix A

Secondly, to evaluate the result of land-use classification, test areas for each cover type were selected from the image based on the ground land-cover information. All test areas were classified again according to the single spectral signatures. A classification error matrix was then calculated to assess the classification accuracy.

2.2.2 Calculation of Environmental Parameters Based on the SEBAL Model:

16 environmental parameters were calculated based on Surface Energy Balance Algorithm for Land (so called SEBAL model, Bastiaanssen etl al., 1998a) to compare the environmental characteristics among various land-use types. They were cosine of solar incidence angle ($cos\theta$), twenty-four hour extraterrestrial radiation (Ra_{24}), surface albedo at the top of atmosphere (α_{toa}), surface albedo (α_0), normalized difference vegetation index ($NDVI$), emissivity (ε_0), surface temperature (T_0), transmittance (τ_{sw}), air density (p_{air}), aerodynamic resistance to heat transport (r_{ah}), estimating friction velocity ($u*$), surface roughness for momentum transport, (z_{om}), net radiation (Rn), soil heat flux (G_o), sensible heat flux (H), and evapotranspiration (ET_{24}). However, because even a thin layer of shadow or cloud can considerably drop the thermal band readings and cause large errors in calculating environmental parameters (Morse et al., 2000), 2 cover types such as shadow and cloud within the study site were masked out.

2.2.3 Investigation of Ecosystem Classification at Various Scales on Environmental Parameters: During the process, land-use types were regarded as the dependent variables and 16 environmental parameters obtained from the SEBAL procedure were regarded as the explanatory variables. Stepwise discriminate analysis was then used to analyze the diacritic parameters for discriminating 5 land-use types, and further to investigate the effect of ecosystem classification at various scales (including northern Taiwan, 12 geographic climate zones, and 7 watersheds) on environment parameters.

3. RESULTS

3.1 Classification of the Land-use Map

Figure 4 represented the spatial distribution of selected blocks and test areas. 8 blocks were selected to perform hybrid classification and calculate the spectral signatures of 7 land-use types. They are forestland, building, farmland, baring farmland, water body, cloud, and shadow. On the other hand, 7 test areas were also selected from the image for the evaluation of land-use classification.

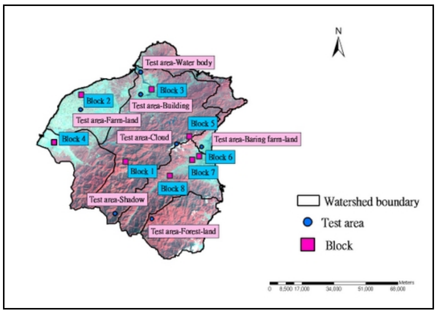


Figure 4. Spatial distribution of the selected blocks and test areas

Figure 5 was the generated map of 7 land-use types. From the classification map, clearly shadow and cloud were occurred and excluded in the further analysis. Besides, Table 1 showed the numbers of pixel and percentages of 5 land-use types (excluding shadow and cloud types). From the table, it is known that forestland occupied most of the study site (42.76%), then baring farmland (20.63%), farmland (19.06%), building (11.41%) and water body (6.14%) was the smallest.

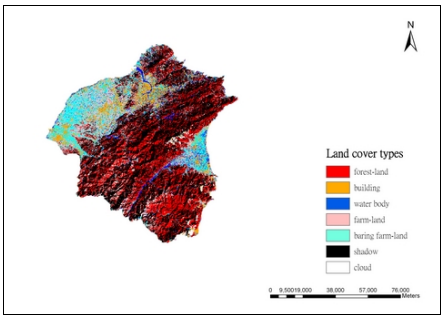


Figure 5. Land-use map of the study area

Land-use types	Numbers of pixel	Percentage of each land-use
Forestland	2844976	42.76%
Building	758939	11.41%
Water body	408455	6.14%
Farmland	1268266	19.06%
Baring farmland	1372659	20.63%
Total	6653295	100%

Table 1. Numbers of pixel and percentages of 5 cover types (excluding shadow and cloud types)

As for the evaluation of classification accuracy, Figure 6 generated by the selected test areas showed that most errors were occurred in 3 kinds of land-use types (i.e., building, baring farmland and water body). For example, building and baring farmland were not separated easily because both types might have the similar spectral reflectance; water body was classified into baring farmland due to some dried holms existing in the river channels; and baring farmland which filled with water might be classified into water body.

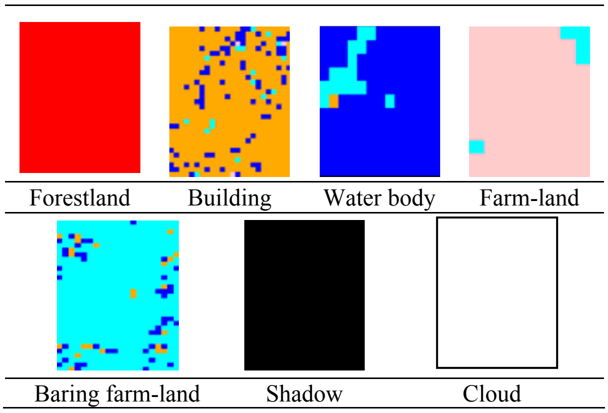


Figure 6. Classification of test areas

Land-use types	Accuracy of test area
Forestland	100%
Building	88.58%
Water body	88.81%
Farmland	94.80%
Baring farmland	89.85%
Shadow	100%
Cloud	100%
Total	100%

Table 2. Accuracy of test areas

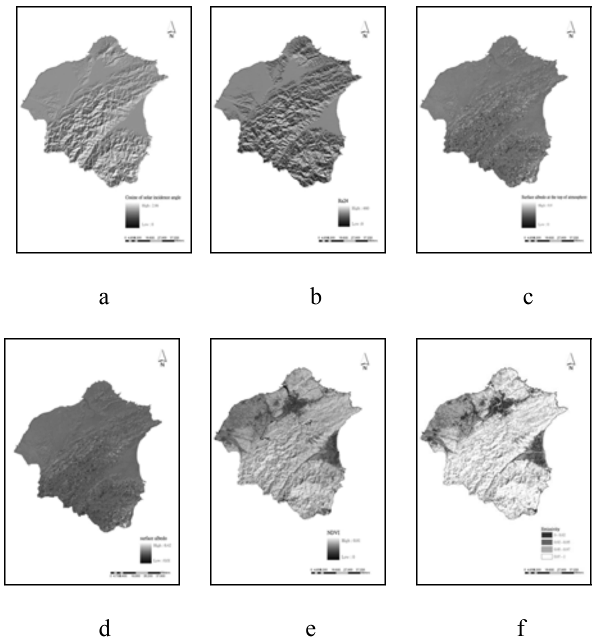
Table 2 was the classification accuracy of test areas among various land-use types. It is clear that the land-use types of forestland, water body, shadow and cloud were 100% accuracy. Building, farmland, and baring farmland are 88.58%, 89.85%, and 88.81%, respectively. In addition, the error matrix obtained from 7 individual test areas was shown as Table 3. It pointed out that the overall accuracy was about 93.19%. This result implied that the land-use map generated by hybrid classification was suitable for investigating the effect of ecosystem classification systems at various scales on environmental parameters.

	Forestland	Building	Water body	Farmland	Baring farmland	Shadow	Cloud	Total of rows
Forestland	238	0	0	0	0	0	0	238
Building	0	659	64	3	14	0	0	744
Water body	0	1	127	0	15	0	0	143
Farmland	0	0	0	91	0	0	0	96
Baring farmland	0	23	42	0	593	0	0	660
Shadow	0	0	0	0	0	336	0	336
Cloud	0	0	0	0	0	0	323	323
Total of Columns	238	687	233	98	622	336	323	2540
Overall accuracy	(238+659+91+593+127+323+336) / 2540 * 100% = 93.19 %							

Table 3. Error matrix obtained from test areas

3.2 Difference of Environmental Parameters among Various Land-use Types

Figure 7 was the generated maps of 16 environmental parameters using SEBAL model. If forestland was taken as a basis and compared the difference of environmental parameters with other land-use types, the result pointed out that forestland had the higher value with cosine of solar incidence angle, twenty-four hour extraterrestrial radiation, net radiation, normalized difference vegetation index, emissivity, estimating friction velocity, surface roughness for momentum transport, sensible heat flux, soil heat flux, evapotranspiration, and had the lower value with transmittance, air density, surface albedo, surface albedo at the top of atmosphere, aerodynamic resistance to heat transport, surface temperature.



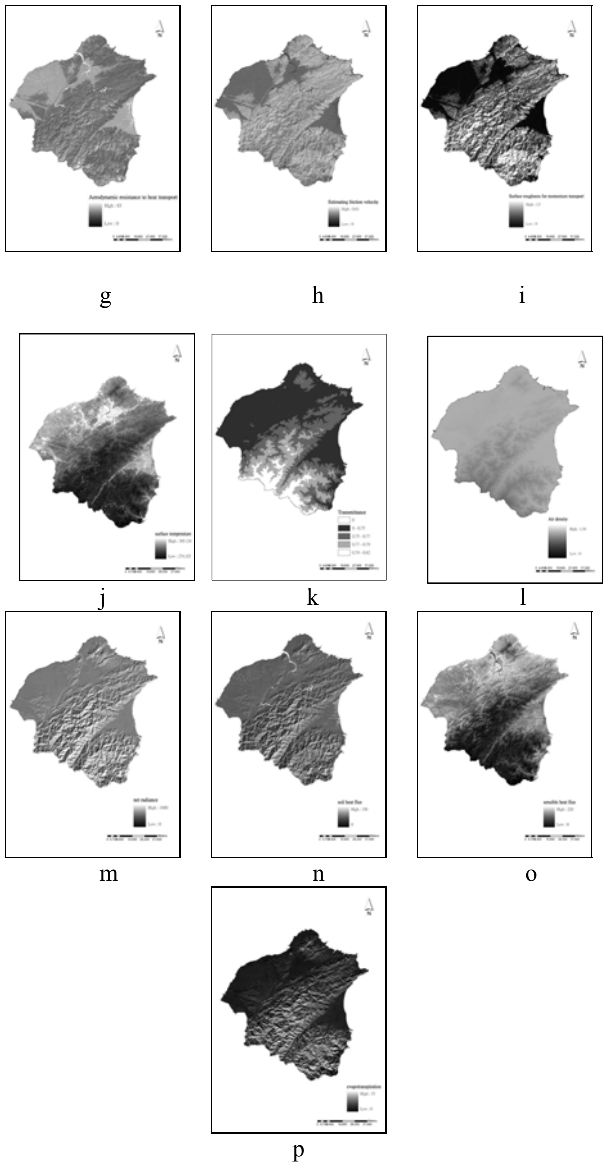


Figure 7. Maps of 16 environmental parameters

(a: cosine of solar incidence angle; b: twenty-four hour extraterrestrial radiation, c: surface albedo at the top of atmosphere; d: surface albedo; e: normalized difference vegetation index; f: emissivity; g: surface temperature; h: transmittance; i: air density; j: aerodynamic resistance to heat transport; k: estimating friction velocity; l: surface roughness for momentum transport; m: net radiation; n: soil heat flux; o: sensible heat flux; p: evapotranspiration)

3.3 Effect of Ecosystem Classification Systems at Various Scales on Environmental Parameters

Table 4 was the output after the stepwise discriminate analysis. It indicated that the required parameters and the numbers of parameters for discriminating 5 land-use types varied with different ecosystem classification systems at various scales. However, no matter what kind of spatial scales and classification systems were used, both *NDVI* and ε_0 parameters were extracted in the stepwise discriminate analysis. Obviously, these 2 parameters can be regarded as the most significant factors.

Spatial scales		Selected parameters
Northern Taiwan		$NDVI\ z_{om}\ \varepsilon_0\ \alpha_0\ R_n\ G_o\ r_{ah}\ p_{air}\ \tau_{sw}\ u^*$
Geographic climate method	Unit 1	$NDVI\ T_0\ \varepsilon_0\ \alpha_{toa}\ z_{om}\ r_{ah}\ H\ u^*\ \tau_{sw}\ \alpha_0\ ET_{24}\ R_n\ Ra_{24}\ G_o$
	Unit 2	$NDVI\ T_0\ z_{om}\ r_{ah}\ \varepsilon_0\ u^*\ \alpha_0\ G_o\ R_n\ H\ \tau_{sw}\ \alpha_{toa}\ ET_{24}$
	Unit 3	$NDVI\ z_{om}\ \varepsilon_0\ r_{ah}\ \alpha_0\ cos\theta\ H\ G_o\ R_n\ ET_{24}$
	Unit 4	$NDVI\ T_0\ z_{om}\ r_{ah}\ \varepsilon_0\ G_o\ \alpha_0\ R_n\ u^*\ H\ \tau_{sw}$
	Unit 5	$z_{om}\ T_0\ u^*\ cos\theta\ H\ NDVI\ \tau_{sw}\ \alpha_0\ G_o\ R_n\ r_{ah}\ \varepsilon_0$
	Unit 6	$NDVI\ z_{om}\ T_0\ u^*\ r_{ah}\ \varepsilon_0\ R_n\ ET_{24}\ \alpha_0\ \alpha_{toa}\ G_o$
	Unit 7	$z_{om}\ cos\theta\ NDVI\ T_0\ H\ \tau_{sw}\ \varepsilon_0\ u^*\ r_{ah}$
	Unit 8	$z_{om}\ T_0\ H\ G_o\ \alpha_{toa}\ \varepsilon_0\ NDVI\ \tau_{sw}\ u^*\ r_{ah}\ R_n$
	Unit 9	$NDVI\ \varepsilon_0\ T_0\ cos\theta\ \tau_{sw}\ \alpha_0\ H\ z_{om}$
	Unit 10	$NDVI\ T_0\ \tau_{sw}\ \varepsilon_0\ z_{om}\ r_{ah}\ u^*\ G_o\ \alpha_0\ R_n$
	Unit 11	$NDVI\ T_0\ \varepsilon_0\ H\ \alpha_0\ \tau_{sw}\ z_{om}\ u^*\ \tau_{sw}\ r_{ah}\ G_o\ R_n$
	Unit 12	$NDVI\ T_0\ \tau_{sw}\ cos\theta\ \varepsilon_0\ G_o\ R_n\ \alpha_0\ \alpha_{toa}\ Ra_{24}\ p_{air}\ H\ z_{om}$
Watershed division method	Unit 1	$NDVI\ \varepsilon_0\ z_{om}\ r_{ah}\ G_o\ cos\theta\ p_{air}\ R_n\ Ra_{24}$
	Unit 2	$NDVI\ z_{om}\ \varepsilon_0\ \alpha_0$
	Unit 3	$r_{ah}\ \varepsilon_0\ NDVI\ H\ T_0\ z_{om}\ \tau_{sw}\ ET_{24}\ p_{air}\ R_n\ cos\theta$
	Unit 4	$z_{om}\ NDVI\ \varepsilon_0\ T_0\ Ra_{24}\ \alpha_0\ R_n\ u^*\ r_{ah}\ H\ \tau_{sw}\ G_o\ ET_{24}$
	Unit 5	$NDVI\ z_{om}\ \varepsilon_0\ u^*\ r_{ah}\ T_0\ ET_{24}$
	Unit 6	$NDVI\ r_{ah}\ \tau_{sw}\ u^*\ \varepsilon_0\ G_o\ R_n\ H\ p_{air}\ Ra_{24}$
	Unit 7	$NDVI\ \varepsilon_0\ z_{om}\ \alpha_0\ r_{ah}\ G_o\ cos\theta\ \alpha_{toa}$

Table 5. Stepwise discriminate analysis under different ecosystem classification systems at various scales

4. CONCLUSIONS

This study integrated remote sensing techniques, SEBAL model and multivariate analysis to assess the effect of ecosystem classification systems at various scales on environmental parameters. The result can be concluded as follows.

(1) The accuracy of land-use classification evaluated by test areas was 93.19%. This implies that hybrid classification is a suitable approach to generate a land-use map. It indeed aims at improving the accuracy or efficiency (or both) of the classification process.

(2) Values of environmental parameters among various land-use types were different. In this study, forestland had higher value with cosine of solar incidence angle, twenty-four hour extraterrestrial radiation, net radiation, normalized difference vegetation index, emissivity, estimating friction velocity, surface roughness for momentum transport, sensible heat flux, soil heat flux, evapotranspiration, and had lower value with transmittance, air density, surface albedo, surface albedo at the top of atmosphere, aerodynamic resistance to heat transport, surface temperature. Besides, the required parameters and the numbers of parameters for discriminating 5 land-use types were also different under different ecosystem classification systems at various scales. But NDVI and emissivity seem to be the most significant parameters no matter what kind of spatial scales and classification systems.

From above conclusions, clearly spatial scales and ecosystem classification systems did affect the estimation of environmental parameters. Also, their effects can be investigated by integrating remote sensing techniques, SEBAL model and multivariate statistical analysis. As stated previously, the quantified environmental parameters can represent the characteristics of ecosystems and indicate the change of environment. Therefore, the result obtained from this study can be extended in the future studies of global environment change and forest resource management.

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