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The Utilization of Google Earth Images as Reference Data for The Multitemporal Land Cover Classification with MODIS Data of North Korea

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Abstract : One of the major obstacles to classify and validate Land Cover maps is the high cost of acquiring reference data. In case of inaccessible areas such as North Korea, the high resolution satellite imagery may be used for reference data. The objective of this paper is to investigate the possibility of utilizing QuickBird high resolution imagery of North Korea that can be obtained from Google Earth data via internet for reference data of land cover classification. Monthly MODIS NDVI data of nine months from the summer of 2004 were classified into L=54 cluster using ISODATA algorithm, and these L clusters were assigned to 7 classes - coniferous forest, deciduous forest, mixed forest, paddy field, dry field, water, and built-up areas - by careful use of reference data obtained through visual interpretation of the high resolution imagery. The overall accuracy and Kappa index were 85.98% and 0.82, respectively, which represents about 10% point increase of classification accuracy than our previous study based on GCP point data around North Korea. Thus we can conclude that Google Earth may be used to substitute the traditional reference data collection on the site where the accessibility is severely limited.

Key Words : Land cover classification, Classification accuracy assessment, Google Earth, QuickBird, MODIS, North Korea.

1. Introduction

Land cover (LC) is one of key factors for estimating net primary production, anthropogenic impact on global environment, and so on (Matsuoka, 2001). The pace of land cover change of the world, including North Korea, is very fast. The economic condition of North Korea has been deteriorating severely after the collapse of communism in the East European bloc countries. To make matters worse great flooding of 1990s destructed much of the agricultural fields and food production capacity of the country. Thus much of the steep slopes of the country have destroyed by large-scale slash-and-burn practices of local residents (Palm, 2005), and the agricultural fields on steep slope of greater than 15% increased by 322,000ha from 2001 to 2005 (Kim, 2006). The collection of accurate and timely information on the status and trend of land degradation of North Korea is essential for the forest

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restoration of the country.

From the 1990s, several scientific researches have been carried out for the land cover mapping of North Korea using remote sensing. Lee (1994) tried to classify primary vegetation cover types all over the Korean Peninsula using the multi-temporal Advanced Very High Resolution Radiometer (AVHRR) imagery. Kim (2000) monitored the vegetation activity of the Korean peninsula using AVHRR. Though AVHRR data have very high temporal resolution compared to other remote sensors, the coarse spatial resolution of 1km is a problem. Lee *et al.*, (1998) used Landsat TM data for forest classification and forest growing stock estimation of North Korea. Lee *et al.*, (1999) used Landsat TM data covering three different time periods to detect forest cover changes of the province of Pyongyang and Heasan in North Korea. However, the land cover mapping with a single temporal image can not take into account the phenological characteristics.

Land cover classification with multi-temporal MODIS data may be used to overcome the shortcomings of above mentioned researches. Kim *et al.* (2007) investigated the optimal land cover classification algorithm for the monitoring of North Korea with MODIS multi-temporal data. They showed that ISODATA and SMA algorithm resulted in a higher classification accuracy of forest and agricultural categories, but SOM algorithm resulted in the highest overall classification accuracy of 73.57%.

Accurate reference data is essential to evaluate land cover classification with remote sensing. Types of ground truth data include field survey data, aerial photographs, airborne video data, and satellite imageries. Aerial photographs have long been used for LC map production, as a mapping base and more recently as a source of higher-resolution reference data for the construction of error matrix. But the availability of reliable reference data for the land cover classification in many developing countries may be severely limited (Sydenstricker-Neto, J., *et al.*, 2004). For example, historical aerial photographs of North Korea are not available to civilian researchers, and the ground visit with GPS receivers is prohibited by the dictatorial government. Due to the limits of reference data in North Korea, many land cover classification researches with remote sensing could not build error matrix, and only could compare the outcomes with various historical or statistical data (Lee, 1994; Lee *et al.*, 1998; Lee *et al.*, 1999).

Kim *et al.* (2007) collected ground truth data with GPS receivers by visiting areas close to the national boundaries of North Korea, including China, Russia, and South Korea. However reference data for land covers can only be found inside the country can not be obtained by this approach. Therefore, the objective of this paper is to investigate the applicability of high resolution remote sensing data provided by Google Earth for the land cover classification and accuracy test of North Korea where reliable ground truth data collection is nearly impossible.

2. Methods

1) MODIS Dataset

The Moderate Resolution Imaging Spectroradiometer (MODIS) offers an opportunity for detailed, large area Land use/Land cover characterization by providing global coverage with high temporal resolution (1~2 days) and intermediate spatial resolution (250m). It includes a time series of visible red (620-670 nm) and near infrared (841-876 nm) surface reflectance (Justice & Townshend, 2002; Wardlow, *et al.*, 2007).

Monthly MODIS data of nine months from June of 2004 to May of 2005 were generated by applying Maximum Value Composite (MVC) of the Normalized Difference Vegetation Index (NDVI) using 65 MODIS 1B images with 250m resolution acquired from Japan MODIS Data Service Centre (http://webmodis.iis.u-tokyo.ac.jp). Geometric correction parameters were set UTM projection (Zone 52N) and WGS 84 Datum. The NDVI is a normalized difference measure comparing the near infrared and visible red bands defined by the formula.

$$\mathrm{NDVI} = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}} / \rho_{\mathrm{NIR}} + \rho_{\mathrm{red}})$$

But monthly NDVI data that might cause severe classification errors were excluded from the DB. Monthly NDVI data from December of 2004 to February of 2005 were excluded due to snow coverage. Monthly NDVI data of July of 2005 were also excluded from the DB because NDVI monthly MVC could not completely remove cloud cover of the extraordinarily rainy month.

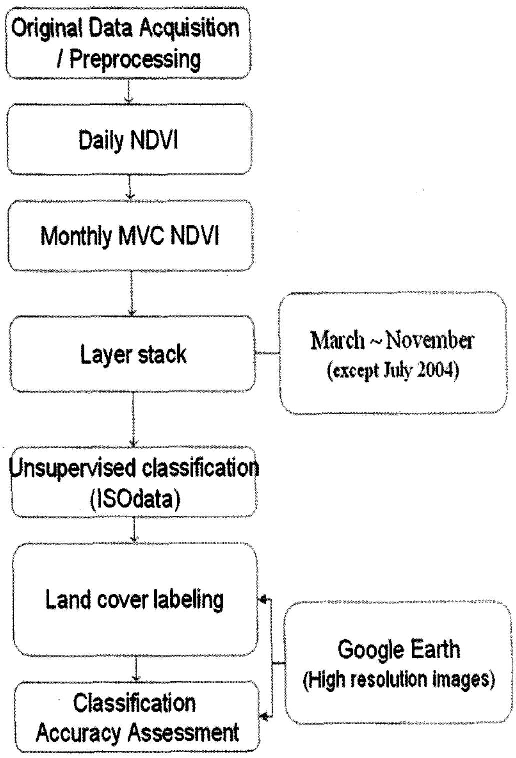

Fig. 1. Flow diagram of data processing.

The classification process began with an unsupervised classification using monthly MVC NDVI maps. The Multitemporal monthly MVC of NDVI data were classified with Iterative Self-Organizing Data Analysis (ISODATA) algorithm with 100 iterations, a widely used unsupervised clustering algorithm (Fig. 1).

2) Google Earth

Since Google Earth launched in 2005, many people have been using Google Earth to explore the world around them. It maps the earth by the superimposition of images obtained from satellite imagery, aerial photography, and GIS 3D globe (http://en.wikipedia.org/). Most land is covered with at least 15 meters of resolution. But insets of very high resolution satellite images and Large Digital Globe update are provided for many cities and areas with special interest among intelligent agencies (http://earth.google.com). The highest resolution satellite imagery currently available to the public is provided by *QuickBird*, launched on October 18, 2001, and operated by Digital Globe, Inc (Lillesand, 2004). For more professional uses, Google Earth Pro allows us to import the GIS files such as .shp and .tab through the GIS Data Importing Module.

The locational accuracy of Google Earth data was tested by using GPS coordinates of five points in South Korea. The internal coordinates system of Google Earth is based on the World Geodetic System of 1984 (WGS84) datum. The RMS error of the test data was less than 1 m in the surface of the earth. Therefore, we can select reliable reference data by using cursors from the Google Earth data on our computer screen.

3) Reference Data Collection

Reference data were used for two purposes in this paper. The first one is to use for the labelling of clusters resulting from unsupervised classification. Since we had very limited knowledge of the study area, high quality reference data obtained through visual interpretation of the Google Earth imagery could be used for the labelling process. Second, reference data is essential to develop error matrix. Thus, sufficient numbers of reference data for each class should be selected by the visual interpretation of high resolution imagery on the Google Earth.

There are currently 147 QuickBird imagery obtained between the years of 2002~2007 on the Google Earth of North Korea, which covers about 30% of the land area. But we selected 99 QuickBird images obtained between 2004~2005 in order to match the time of MODIS data for this research. The yellow and red rectangles on the Google Earth show scenes obtained in 2004 and 2005, respectively (Fig. 2).

The number of QuickBird scenes on the Google Earth sampled for reference data for land cover classification with MODIS imagery is shown on the Table 1. The number of images obtained during growing seasons, from May to October, is 35 scenes, and the rest or 64 scenes were obtained during vegetation dormancy. Such seasonal imbalance is mainly caused by two reasons. First, the collection of visual band imagery during plant growing seasons is usually limited because of heavy and frequent cloud cover. Second, the collection of high resolution imagery or photography of dormant seasons is preferred by many intelligent officers for the detection of military installations or structures.

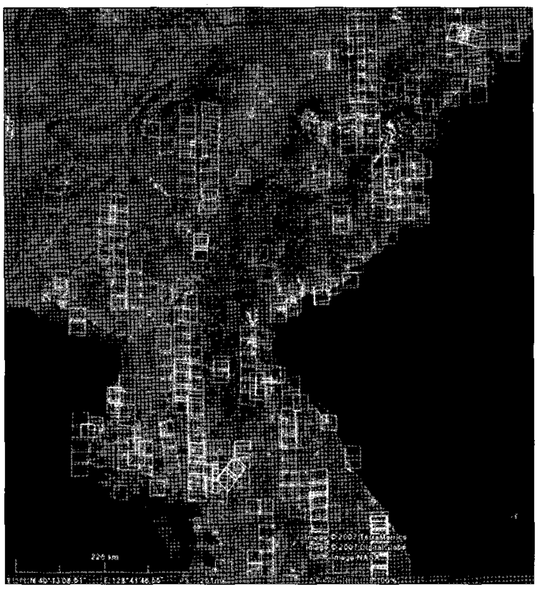

Fig. 2. QuickBird Scenes covering North Korea, 2004~2005.

Seventy-three reference pixels were extracted through the visual interpretation of QuickBird imagery of the Google Earth by using high-resolution satellite imagery interpretation keys (Lillesand, 2004).

Coniferous forests are recognisable on Google Earth images by their dark colour, which stands out from the brightness of deciduous forest. We mainly selected sample points from dormant season images to facilitate visual detection from high resolution imagery. Based on the crown coverage of leaves on winter imagery, we can easily discriminate evergreen

Table 1. Number of QuickBird Scenes Used for Reference Data Collection.

	2004	2005	TOTAL
Jan.	6	1	7
Feb.	6	5	11
Mar.	14	12	26
Apr.	11		11
May	1	7	8
Jun.	12		12
Jul.			
Aug.	1	4	5
Sep.			
Oct.	6	4	10
Nov.	1	7	8
Dec.	1		1
TOTAL	59	40	99

forest and deciduous forest. The interpretations were based on the majority of a 3 × 3 pixel moving window (Congalton and Green, 1999; Khorram, 2004). We tried to select homogeneous patches for each land cover type, and reference site was located at the centre of the 3 × 3 window.

The visual interpretation of paddy field and dry field is based on the presence or absence of surface water during growing season. Paddy field is land prepared for rice cultivation. There are flat surfaces with irrigation channels and surfaces periodically flooded. This category is easily identified using multitemporal images, i.e. spring images, on which the rice field area always flooded, and summer images, where the young plants can be located by the very high degree of reflection in the near infrared spectral band (EEA, 2003).

Built-up areas and waters are clearly visible on many aerial and satellite images (Lillesand, 2004). The built-up class characterized by the high percentage of construction materials. The water class is all areas of open water. Areas of open water produce a dark blue image. The dark colour and uniform smooth texture of the open water in distinct contrast with the lighter tones of the surrounding vegetation.

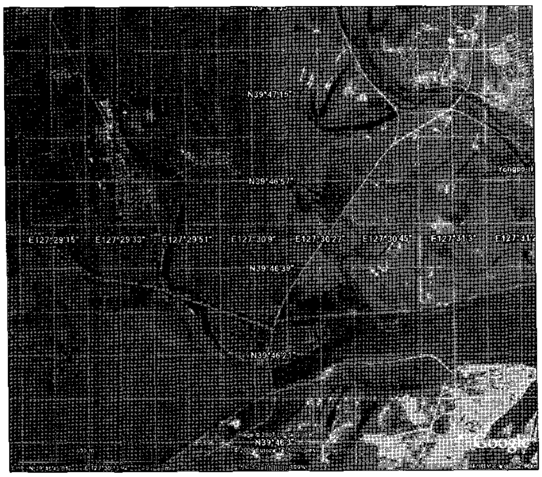

Fig. 3. Reference pixel selection for Water and Paddy field.

Latitude and longitude grid lines provided in Google Earth window are useful to select the centre of reference pixels (Fig. 3). The selection of reference pixels of water and paddy field is shown in the Fig. 3. We can see turbid water surface at the lower-left window and paddy field at the upper-right window. But windows of 2 × 3 were also used for rare classes such as water so as to select enough numbers of reference data.

4) Classification Scheme

A classification scheme has two critical components: (1) a set of labels, and (2) a set of rules or definition such as a dichotomous key for assigning labels (Green, 2004). We utilized a seven-category LC classification hierarchy (Table 2).

The water class is all areas of open water, generally with less than 25% vegetation. The built-up class characterized by the high percentage of construction materials. The coniferous class contained at least 75% conifer and less than 25% of deciduous. The deciduous class had at least 75% deciduous and no more than 25% coniferous. All other forest types were labelled as a mixed forest.

Visual interpretation of bare soil from high resolution Google Earth is difficult, and the classification accuracy of bare soil classes based on the MODIS 250m pixel size is very low, too. Therefore, bare soil class is not included for this

Table 2. Classification hierarchy.

	CLASS
FOREST	Coniferous Forest
	Deciduous Forest
	Mixed Forest
CROP LAND	Paddy Field
	Dry Field
WATER	Water
BUILT-UP	Built-up

research, and they may be classified as built-up areas. Land cover of grassland was not included in this research because we could not acquire enough reference data for the class. Therefore, large grasslands, if any in North Korea, may be classified as deciduous forest.

The reference data are helpful to define intermediate classes, which were easier to relate to the spectral information. Interactive manipulation of spectral signatures for each class permitted many of the mixed classes to be resolved.

5) Sampling Procedure

A generally accepted rule of thumb is to use a minimum of 50 samples for each LC category in the error matrix (Congalton and Green, 1999). If the area is especially large or the classification has a large number of LC categories, for example more than 12 categories, the minimum number of samples should be increased to 75 to 100 samples per category (Congalton and Green, 1999). In this study sample points were selected using a stratified random sampling design, stratified by LC area for each of the accuracy assessment. Research by Conglaton (1988) indicates that random and stratified random samplings are the optimal sampling designs for accuracy assessment.

Primary sample unit (PSU) were 3×3 km quadrangle area. Sample units are the portion of the landscape that will be sampled for the accuracy assessment. A stratified random sampling design was incorporated with samples apportioned by LC area, using a minimum sample size of n = 50 for rare classes. After evaluation of selected sample points in each reference data set, an error matrix was constructed. It compares map class labels with reference data labels for each LC classification. Overall map accuracy and class-specific user and producer accuracies were calculated for each class.

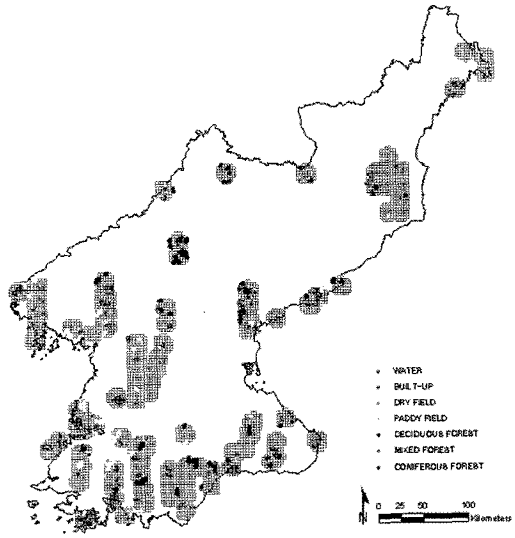

Fig. 4. Primary Sample Unit (PSU) and selected sample sites.

In this study, 15~35 PSU per class were selected across all the quadrangles, and 215 PSU for seven land cover classes were selected. The total number of reference samples was 1049 pixels (Fig. 4). The reference pixels were used as validation data for assessing the accuracy.

3. Results and Discussion

1) Land Cover Classification

The monthly NDVI data set were classified by using unsupervised classification method, and later labelled based on the QuickBird imagery obtained from the Google Earth images of 2004~2005. The number of clusters was 54. Each of the 54 spectral classes was carefully evaluated by its statistics and reference data, and merged into one of 7 cover type classes; coniferous forest, deciduous forest, mixed forest, paddy field, dry field, water, and built-up areas.

The final land cover classification is shown in Fig. 5, and the outcomes can be summarized as follows.

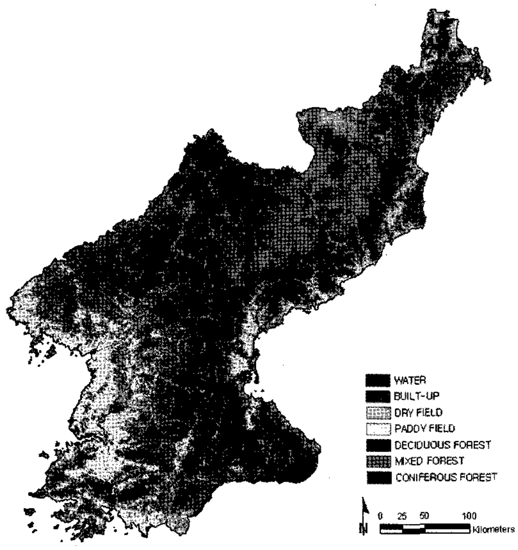

Fig. 5. Land cover classification.

First, forest cover occupied 8,177,814ha, or 66.74% of the country. Total area of forest of this paper is about 269,200 ha less than that of the estimation of the Korea Forest Research Institute in 1991. This might reflect the recent trend of forest destruction of North Korea. The percentage occupied by coniferous, mixed, and deciduous forests was 8.30%, 11.65%, and 46.80%, respectively, of the country. Second, agricultural fields occupied 3,811,651ha, or 31.11% of the country. The percentage for dry field and paddy field was 23.20% and 7.91%, respectively, of the country. The total area of agricultural field was very close to that of the FAO (2005), but the percentage of dry field in this paper increased significantly. This might be caused both by the increase of dry filed on steep slopes expanded through slash-and-burn practice and by the decrease of paddy fields due to the massive flooding of 1990s. Finally, built-up areas and water surface covered 1.53% and 0.62%, respectively, of the country. The percentage of built-up areas was smaller than that of the Kim (2006), and further research is necessary to clarify the difference.

2) Accuracy Assessment

The typical land cover classification accuracy test is carried out by constructing error matrix that shows the percentage of each class correctly classified by

Table 3. Error Matrix of Land Cover Classification.

	Reference Data *unit; pixel (percent)*							
	Coniferous.	Deciduous.	Mixed.	Paddy.	Dry.	Built-up	Water	Total
Coniferous Forest	75(72.12)	3(1.26)	0(0.00)	0(0.00)	0(0.00)	0(0.00)	0(0.00)	78(7.44)
Deciduous Forest	15(14.42)	234(97.91)	12(9.60)	0(0.00)	2(1.74)	0(0.00)	5(6.76)	268(25.55)
Mixed Forest	6(5.77)	2(0.84)	109(87.20)	0(0.00)	1(0.87)	0(0.00)	4(5.41)	122(11.63)
Paddy Field	1(0.96)	0(0.00)	0(0.00)	266(93.99)	3(2.61)	2(1.83)	3(4.05)	275(26.22)
Dry Field	7(6.73)	0(0.00)	4(3.20)	12(4.24)	107(93.04)	25(22.94)	14(18.92)	169(16.11)
Built-up	0(0.00)	0(0.00)	0(0.00)	3(1.06)	2(1.74)	75(68.81)	12(16.22)	92(8.77)
Water	0(0.00)	0(0.00)	0(0.00)	2(0.71)	0(0.00)	7(6.42)	36(48.65)	45(4.29)
Total	104(100.00)	239(100.00)	125(100.00)	283(100.00)	115(100.00)	109(100.00)	74(100.00)	1049(100.00)
	PRODUCER'S ACCURACY				USER'S ACCURACY			
Coniferous Forest	75/104 = 72.12%				75/78 = 96.15%			
Deciduous Forest	234/239 = 97.91%				234/268 = 87.31%			
Mixed Forest	109/125 = 87.20%				109/122 = 89.34%			
Paddy Field	266/283 = 93.99%				266/275 = 96.73%			
Dry Field	107/115 = 93.04%				107/169 = 63.31%			
Built-up	75/109 = 68.81%				75/92 = 81.52%			
Water	36/74 = 48.65%				36/45 = 80.00%			
	Overall Accuracy = (902/1049) 85.9867%							
	Kappa Coefficient = 0.8291							

using reference data. Matches between the reference data and classified outcomes were coded as either agreed (1) or disagreed (0), and the error matrix is shown on the Table 3. Overall classification accuracy and Kappa index was 85.99% and 0.8291, respectively. Accuracy for land cover classes ranged from 48.65% to 97.91%. The deciduous forest showed the highest accuracy, but the producer' s accuracy of coniferous and mixed forest was 72.12% and 87.20%, respectively. The accuracies for paddy and dry fields were over 93% level. Such high accuracy for vegetation related classes demonstrates the advantages of using multitemporal classification of monthly MODIS data. The water class showed the lowest classification accuracy of only 48.65%. This might be caused by relatively smaller number of reference data for water and diverse reflectance characteristics caused by the difference of turbidity and mixed pixel effect at the edge of water surface. The lower classification of 68.81% for built-up areas also might demonstrate that the diverse land cover characteristics of urban areas and relatively smaller number of reference pixels for this class.

4. Conculsions

Outcomes of this paper can be summarized as follows. First, the land cover classification with multi-temporal MODIS data of North Korea produced a very reliable LC map. Overall classification accuracy and Kappa Coefficient was 85.99% and 0.8291, respectively. Second, Google Earth can be an economic and accurate source of reference data for study areas where the collection of ground truth data is prohibited by government regulations such as North Korea. By using QuickBird imagery provided by the Google Earth, we could easily select reference data of 1049 pixels, and statistically meaningful number of samples for land cover classes of coniferous forest, mixed forest, deciduous forest, dry field, paddy field, water, and built-up areas were collected. We could save the cost for the field trip for reference data collection by using the Google Earth, and the overall land cover classification accuracy for this paper of 85.99% is about 10% higher than our previous land cover classification based on GPS data of adjacent areas of North Korea.

There are some limits to reference data collection with Google Earth. First, not enough numbers of reference data for water surface, glassland, and bare soil could be selected. We could increase the classification accuracy of such classes if more reference data were selected Kappa index. Second, the availability of more high resolution imagery acquired during growing seasons could increase the classification accuracy of agricultural fields, bare soil, and grassland.

Acknowledgement

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