

Comparison of Three Land Cover Classification Algorithms - ISODATA, SMA, and SOM - for the Monitoring of North Korea with MODIS Multi-temporal Data

Do-hyung Kim*[†], Seung-gyu Jeong**, and Chong-hwa Park***

*Environmental Planning Institute, Seoul National University

**Environmental Planning Institute, Seoul National University

***Graduate School of Environmental Studies, Seoul National University

Abstract : The objective of this research was to investigate the optimal land cover classification algorithm for the monitoring of North Korea with MODIS multi-temporal data based on monthly phenological characteristics. Three frequently used land cover classification algorithms, ISODATA¹⁾, SMA²⁾, and SOM³⁾ were employed for this study; the land cover categories were forest, grass, agricultural, wetland, barren, built-up, and water body.

The outcomes of the study can be summarized as follows. First, the overall classification accuracy of ISODATA, SMA, and SOM was 69.03%, 64.28%, and 73.57%, respectively. Second, ISODATA and SMA resulted in a higher classification accuracy of forest and agricultural categories, but SOM performed better for the built-up area, bare soil, grassland, and water. A possible explanation for this difference would be related to the difference of sensitivity against the vegetation activity. This would be related to the capability of SOM to express all of their values without any loss of data by maintaining the topology between pixels of primitive data after classification, while ISODATA and SMA retain limited amount of data after normalization process. Third, we can conclude that SOM is the best algorithm for monitoring the land cover change of North Korea.

Key Words : ISODATA, SMA, SOM, MODIS, Multi-temporal Imagery, land cover classification.

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[†] Corresponding Author: Do-Hyung Kim (dhkim76@gmail.com)

- 1) Isodata stands for Iterative Self-Organizing Data Analysis Techniques. This is a more sophisticated algorithm which allows the number of clusters to be automatically adjusted during the iteration by merging similar clusters and splitting clusters with large standard deviations.
- 2) Spectral Mixture Analysis (SMA) separate Unmixing pixels as Linear Spectral Unmixing Model.
- 3) The self-organizing map (SOM) is a subtype of artificial neural networks. It is trained using unsupervised learning to produce low dimensional representation of the training samples while preserving the topological properties of the input space.

1. Introduction

The deterioration of natural environment and agricultural productivity of North Korea has been the topic of many recent researches. But data collection by foreign researchers reflects substantial limitations. The importance of reliable data prior to unifying North and South Korea reinforces the significance of this project. Remote sensing is an essential tool to fulfill the demand for accurate, reliable, and timely data. Land cover classification of North Korea is more difficult than that of South Korea. Because the Plant growing period of North Korea is much shorter, and different spectral characteristics of forest and agricultural areas result from different crop types and cropping practices. To make matters worse, widespread forest degradation and flood damage resulted in similar reflection characteristics of scattered forest, grass land, orchard, and bare soil.

Land cover classification of North Korea promises a solution to many problems. First, the application of supervised classification might be affected by insufficient data. There is no library of spectral characteristics and no ground truth data on North Korea (Kim, 2001). Second, it is difficult to distinguish built-up area and bare soil. There is a significant spectral difference between the South and North Korea because of the difference of species composition and density. These factors, combined with forest degradation, can significantly deteriorate land cover classification accuracy (Sagong, 2000). It is essential to identify proper land cover classification algorithms suitable for the reliable classification of built-up areas and fragmented forest which has no pattern or homogeneity.

There have been several researches of land cover mapping of North Korea with remote sensing. Lee (1997) used single temporal image and vegetation indices. Lee(1999) used vegetation indices and

adopted seasonal environmental factors to classify the land cover of North Korea. But such researches have fundamental limitations. Land cover mapping with a single temporal image can not take into account phenological characteristics of forest and agricultural areas (Jensen, 2000). The non-linear aspect of the North Korean terrain is unsuitable with land cover classification algorithms that normalize the values of spectra. It is difficult to discriminate a deciduous broad-leaf stand from an evergreen-conifer forest with land cover classification algorithms based on the traditional multi-spectral classification of a single season. It is also very difficult to select suitable multi-spectral imagers for the discrimination of agricultural land from barren soil, or wetland from paddy field.

Such limitations can be overcome by employing multi-temporal classification of MODIS data based on the phenological characteristics of the study area. The difference of seasonal growing patterns of vegetation and agricultural cultivation practices can be essential to monitor land cover change over a large area. The classification accuracy between paddy field, water body, and dry field can be remarkably increased.

AVHRR (Advanced Very High Resolution Radiometer) images of NOAA⁴⁾ satellites were applied frequently for land cover mapping of wide scale areas (Weiss and Milich, 1997). Recently, MODIS (Moderate Imaging Spectroradiometer) has replaced the AVHRR data for multi-temporal land cover classification because of its better data quality.

Three land cover classification algorithms were tested and evaluated for the classification of MODIS monthly data. They were ISODATA (Iterative Self-

4) The National Oceanic and Atmospheric Administration (NOAA) is a scientific agency of the United States Department of Commerce focused on the conditions of the oceans and the atmosphere.

Table 1. Summary of Ground Truth Data.

	built -up	paddy -body	field forest	water land	deciduous	conifer	Mixed	grass	wet-	barren	SUM
Gyeonggi-do	12	79	9	60	37	4	63	7	-	7	278
Along the Chinese-N.K. border.	34	37	47	78	77	9	15	84	33	27	471

Organizing Data) algorithm, SMA (Spectral Mixture Analysis), and SOM (Self-Organizing Map), and the details of the selected algorithms will be discussed in the next section.

2. Data and methods

1) MODIS data

The MODIS has 36 bands in an image, and have time resolution of 1~2 day so that it can observe the whole earth every 2 days (King, 2003). The masking of whole Korean peninsula necessary to remove the sea surface was carried out by using the images of Web MODIS web site (<http://webmodis.iis.u-tokyo.ac.jp>) of Tokyo University. The MODIS data with less cloud cover from June of 2001 to May of 2002 were used for this project. Data from January and February were not used for data base construction because snow coverage can deteriorate the accuracy of land cover classification. The level 1b⁵ data of 250m resolution were used. The data set includes the infrared and near infrared bands which can be used to detect photosynthetic activities of vegetation.

2) Ground truth data

The ground truth data were collected in areas close to North Korea. First, as shown in Fig. 1, extensive GPS points were collected along a route in China from the mouth of the Aplok River to Mt. Baekdu, and to the mouth of the Duman River. Southern coastal area of Russia was also included for the

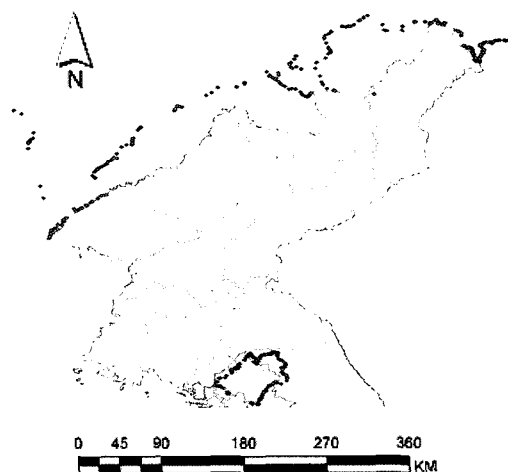


Fig. 1. Location of Ground Truth Data.

ground survey. Second, many GPS points in areas adjacent to DMZ in Cholwon and Yonch'on of South Korea were also collected. Such efforts can minimize errors potentially caused by using unreliable image classification products or secondary data provided by relevant agencies such as the Ministry of Environment and the Korea Research Institute for Human Settlements. Garmin GPS V with 5m of error range was used. Because the spatial resolution of MODIS is 250m, it was important to collect ground truth data of parallel scale. The collected ground truth data were categorized into two groups, and each subset was used for labeling of classified image and accuracy verification of classified results.

It was easy to select GPS points for paddy field,

5) The Level 1B Code generates data products containing calibrated radiances for all 36 MODIS bands and reflectance for the reflective Solar bands (Bands 1 through 19 and 26).

built-up area, and forest that can effectively remove pixel registration error of MODIS data with 250m resolution. On the other hand, not enough numbers of grassland, wetland, and bare soil were selected due to the usual small sized patches.

3. Image classification methods

In this research, Kohonen's⁶⁾ SOM (Self-Organizing Map) technique which is known for its accuracy was applied. SOM is the aggregate of nodes of more than one dimension (Kohonen, 1986). Each node is constituted with units of vectors which points to a random direction at n-dimension space. After the normalization, multi dimensional data is expressed by each node. Using winner-take-all method, the node which has vector value is almost the same with the input data is found. This vector replaces a weight value with actual data. And the nodes which wrap this vector are changed to be a little bit different with the vector. This way, the node studies the how to recognize the vector which is similar with itself. One of SOM's useful features is the ability to maintain topology and to auto-generate the probability of data. Maintaining topology means that it leaves the original relationship between data points after processing. It is a feature needed to the process hyper-spectral image classification because it maintains the relationship between the pixels of the image. Also, SOM continuously creates probability distribution or the statistical model of data and continues this statistical modeling even when there is no complete analytic function (Caudill, 1988). SOM produces better results when applied to the complicated and non-linear patterned terrain like North Korea (Atkinson and Tatnall, 1997).

ISODATA analyzes an image repetitively on the basis of spectral distance. The user inputs the number

of nodes in the beginning, and these nodes become the center of each cluster, and the pixels are combined to the cluster by the critical values which the user has input. After each iteration, the average value of the cluster is calculated by the basis of the spectral location of pixels. This new average values are used in the next iteration. This process is continued until the quantity of value change becomes insignificant.

SMA (Spectral Mixture Analysis) is a technique which interprets the possession ratio of objects which composes each pixel using specific spectral reflection characteristics of various objects mixed in a pixel of image. It is also called spectral unmixing, because it disjoints the components of pixel by its possession ratio of pure components that composes the mixed pixel (Keshava and Mustard, 2002).

1) Classification using ISODATA algorithm

The daily NDVI⁷⁾ images were extracted using collected image data between May 2001 and June 2002. And monthly MVC (Maximum Value Composite) method that selects the maximum value of each pixel from daily NDVI images. Finally, the layers of monthly images were stacked to make a layer-stacked-image and classified it with ISODATA algorithm. The value of parameter ITERATION was set to 100 and MAXIMUM CLASS was set to 60. The results of the classification of 60 classes were labeled into the classes of agricultural, forest, water, built-up, and grassland.

6) Kohonen, T. : invented Self-Organizing Maps algorithm.

7) the Normalized Differenced Vegetation Index (NDVI) is $NDVI = (NIR - R) / (NIR + R)$, The NDVI gives a measure of the vegetative cover on the land surface over wide areas. Dense vegetation shows up very strongly in the imagery, and areas with little or no vegetation are also clearly identified.

2) Classification using SMA algorithm

Using the same collection of NDVI data set used in ISODATA classification, the end members of the objects were selected. Daily fraction image of soil, water, and vegetation were made applying linear mixture model. And monthly images which consists of maximum values of pixels of the same location in each images were made. They were used to make the monthly images by Maximum Value Composite method in order to remove the effects of cloud cover of each pixel. Also layer-stacked-image was made and was classified with ISODATA algorithm. The same values of parameters and the classes of land cover used for ISODATA were also used.

3) Classification using SOM algorithm

Since the top layer of cloud cover has higher reflectance compared to other land cover types, the effect of cloud can be removed from the raw data by using the Minimum Value Composite method. This process can be divided into two stages. First, about 10 daily images with less cloud cover were selected by using the visual inspection method. Then, the effect of clouds was removed from monthly image by taking the lowest value of each pixel in stacked layers. With these monthly images, a layer-stacked-image was made, and it was classified with SOM algorithm. The same values of parameters and the classes of land cover used for ISODATA were also used.

4. Results and discussion

After labeling the classes agricultural, forest, water, and built-up, accuracy verification was performed. The results of image classification can be summarized as follows.

First, the overall classification accuracy and Kappa coefficients of the Self-Organizing Map was 73.5%, and 0.65, respectively. The classification accuracy and Kappa coefficients of the SMA was 64.28% and 0.65, respectively. The classification accuracy and Kappa coefficients of ISODATA was 69.03% and 0.54, respectively.

Second, the accuracy verification made after re-labeling the classes by adding an additional class of grassland showed deteriorated results as illustrated in Table 2. The classification accuracies of and Kappa coefficients of Self-Organizing Map was 48% and 0.32, respectively. The classification accuracies of and Kappa coefficients of SMA was 46% and 0.28, respectively.

Table 2. Classification Accuracy of Three Classification Algorithms. (unit: percent)

	ISODATA	SMA	SOM
Grass	0	8.63	23.74
Forest	41.01	40.29	24.46
Paddy Field	39.57	38.85	28.06
Water body	7.91	8.63	10.07
Built-up	10.79	2.88	12.59
Total	53	46	48

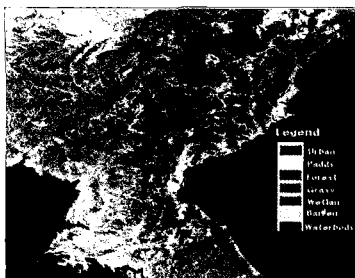


Fig. 2. ISODATA Classification Result.

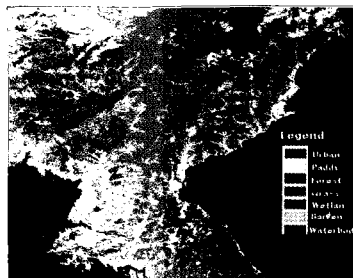


Fig. 3. SMA Classification Result.

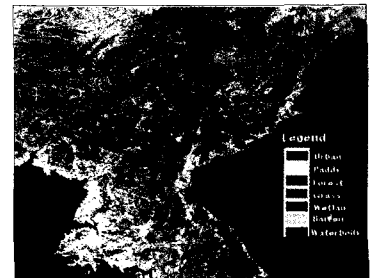


Fig. 4. SOM Classification Result.

The classification accuracies and Kappa coefficients of ISODATA was 53% and 0.39, respectively.

Third, accuracy verification results of land over classes with three algorithms revealed several interesting points. The classification accuracy of grassland with ISODATA, SMA, and SOM was 0%, 8.63%, 24.74%, respectively. The classification accuracy of forest with ISODATA, SMA, and SOM was 41.01%, 40.29%, 24.46%, respectively. The SOM algorithm was better than others in classifying grassland and forest, thus in can be suspected that SOM could discriminate subtle difference between forest and grassland. On the other hand, ISODATA and SMA were less successful in classifying two similar land cover classes like grassland and forest. The basics of SOM are similar with ISODATA, but SOM operates differently. With SOM, the center of cluster with SOM is allowed to be moved for explaining the topological relationship of dataset (Brian, 2001). In the process of the classification

using ISODATA, pixels are assigned to classes by the given nodes and these nodes are not changed through the whole process. So, it was expected that ISODATA would produce better accuracy than using SOM in classifying objects which has linear relationships between pixels, and it would produce less accuracy with fragmented and non-linear objects. As the classification results suggest, SOM has better a capability to distinguish the pixels from each other having delicate differences in spectral value than ISODATA, especially for forest and grassland, even though the overall accuracy was comparatively low.

The classification accuracy of agricultural area by ISODATA, SMA, and SOM was 39.57%, 38.85%, and 28.06%, respectively. This result represents the potential of ISODATA and SMA for the classification of vegetation using multi- temporal NDVI image. This is because NDVI was not used at the classification process by SOM, in order not to lower the dimension of data by normalizing data and

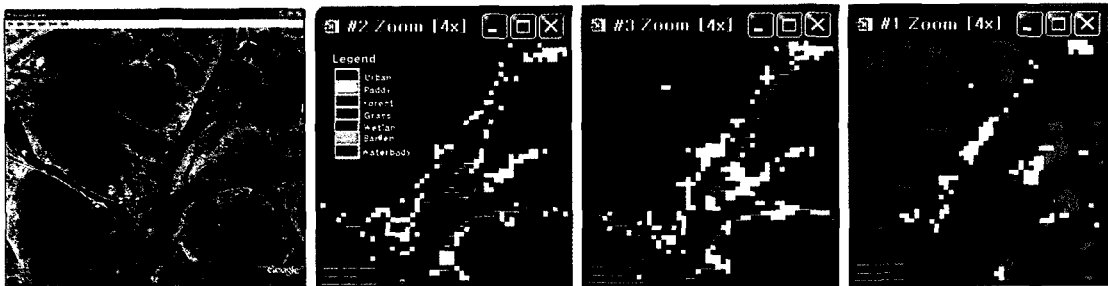


Fig. 5. Algorithm Comparison between ISODATA, SMA, and SOM in Yangsuri.

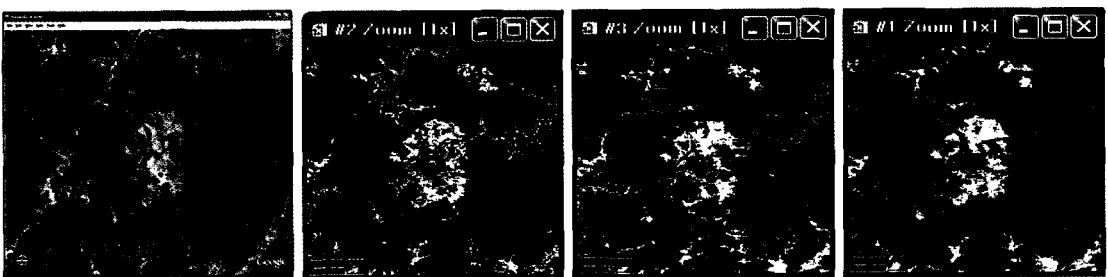


Fig. 6. Algorithm Comparison between ISODATA, SMA, and SOM in ChunChon-municipality.

to maintain the topology between pixels.

The classification accuracy of built-up area by ISODATA, SMA, and SOM was 10.79%, 2.88%, and 12.59%, respectively. The higher accuracy of SOM was due to its better performance for the classification of non-linear objects made by human activities.

The classification accuracy of water body by ISODATA, SMA, and SOM was 7.91%, 8.63%, and 10.07%, respectively. Fig. 5 and Fig. 6 shows the classification results of two test sites, Yangsuri and Chunchon, using three classification algorithms. It shows that SOM is better than other algorithms for water which has a typical non-linear pattern.

5. Conclusions

Three frequently used land cover classification algorithms, ISODATA, SMA, and SOM, were evaluated to select the optimal algorithm for the land cover classification of North Korea. Seven land cover classes - forest, grass, agricultural, wetland, barren, built-up, and water body - were classified with MODIS multi-temporal data.

The outcomes of the study can be summarized as follows. First, the overall classification accuracy of ISODATA, SMA, and SOM was 69.03%, 64.28%, and 73.57%, respectively. This overall performance was unsatisfactory to us. But we concluded that the accuracy level provided a solid evaluation for each classification algorithm. We can employ many classification techniques so as to increase the classification accuracy for an actual land cover classification project. For example, hybrid classification methods that utilize masking of water body or the combination of expert knowledge can reduce classification errors in small patches or linear objects (Lillesand and Kiefer, 2000).

Second, the classification accuracy of each

classification algorithm was affected by different reflectance characteristics. ISODATA and SMA resulted in higher classification accuracy of forest and agricultural area than that of SOM. This is because we used NDVI for the classification process with ISODATA and SMA, which is sensitive to vegetation. The higher percentages of ground truth data for forest and agricultural land might also contributed to the higher classification accuracy than others. But SOM performed better than the two other algorithms for the built-up area, bare soil, grassland, and water. Water and built-up area were confused significantly with ISODATA and SMA algorithms. It was suspected the difference would be related to the difference of sensitivity against the vegetation activity. This would be caused by the capability of SOM to express all of their values without any loss of data by maintaining the topology between pixels of primitive data after classification. Meanwhile, ISODATA and SMA retains limited amount of data after normalization process.

Third, the classification accuracy was also affected by the number of classes, especially two classes with the potential of severe confusion. The addition of grassland resulted in higher accuracy of ISODATA compared to those of SMA and SOM. But SOM produced the highest accuracy when grassland was excluded from the classification. SOM was suitable for the linear patterned and fragmented terrain and performed well for the classification of grassland, bare soil, water, and built-up area.

Fourth, in terms of the convenience of image classification, SOM is better than ISODATA and SMA. An additional stage of NDVI calculation is necessary for ISODATA, and complicated steps for the production of fraction images and the selection of end member for vegetation, soil, and water are necessary for SMA.

Finally, we concluded that SOM was the optimal algorithm for monitoring land cover changes in North

Korea. As presented earlier, SOM algorithm performed well for the classification of non-linear change of natural environment made by human activity. Thus it can be used to perform more detailed researches on forest fragmentation and degradation, and agricultural devastation. Furthermore, the multi-temporal image classification would increase classification accuracy of grassland and bare soil because of the distinct phenological difference of both cover types.

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