CONTINENTAL SCALE LAND COVER CLASSIFICATION USING MODIS SURFACE REFLECTANCE PRODUCTS

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ABSTRACT:

The objective of this study is to develop land cover classification algorithm suited for continental scale like the eastern Asia by using multi-temporal MODIS land reflectance products; Surface Reflectance 8-Day L3 product and Nadir BRDF-Adjusted Reflectance 16-Day L3 product. In this study, land cover maps derived from these two kinds of source data products are generated and compared. Time-domain co-occurrence matrix is introduced as a classification feature that represents time-series signature of land covers. The non-parametric minimum distance classification using Euclidian distance or cosine distance is conducted. As results, Surface Reflectance 8-Day L3 product and Nadir BRDF-Adjusted Reflectance product showed similar classification accuracy of 92%-96% for IGBP-17 land cover categories. Furthermore, it is confirmed that the accuracy is 15%-20% higher than that of MODIS land cover product for the target classification area.

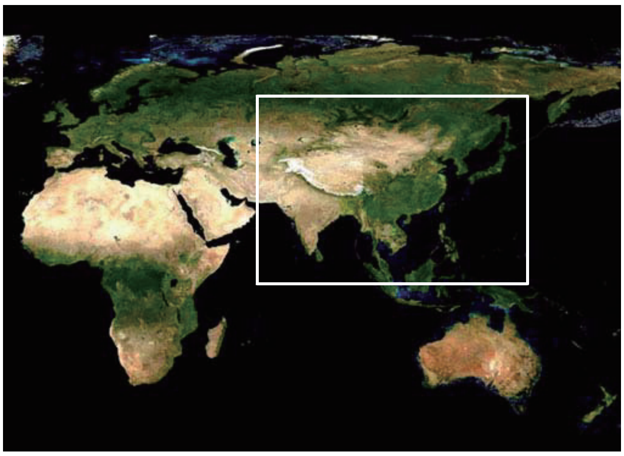
1. INTRODUCTION

Land cover maps of Global and/or continental scale are basic information for many kinds of applications, i.e. global change research, modeling, resource management, etc. Several kinds of global land cover maps has been generated, such as IGBP DISCover Global Land Cover, UMD Global Land Cover, and MODIS Land Cover, etc., and these products have been distributed widely. However, accuracies of these global land maps were not sufficiently high. Most of these land cover maps were generated mainly using NDVI and its seasonal changes. However, NDVI data lose most of information contents which were originally included in many channels.

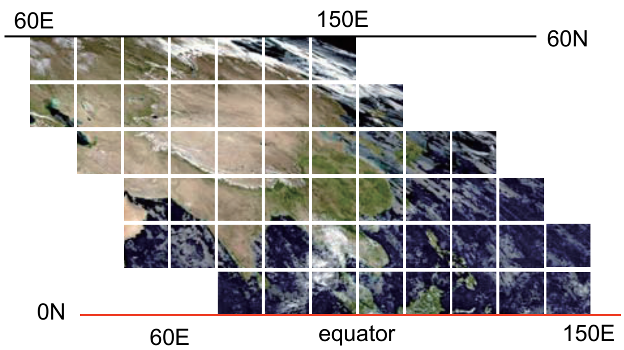
Therefore, we have tried to develop land cover maps suited for the eastern Asia by using multi-temporal MODIS land reflectance products. There are two kinds product of Surface Reflectance 8-Day L3 product and Nadir BRDF-Adjusted Reflectance 16-Day L3 product. Both are composed of 7 spectral bands（620-670nm, 841-876nm, 459-479nm, 545-565nm, 1230-1250nm, 1628-1652nm, and 2105-2155nm） with 500m ground resolution. The former is the atmospheric corrected surface reflectance, while the latter corrects the BRDF effects in addition to the atmospheric correction. In this report, these products are called SR product and NBAR product, respectively.

2. STUDY AREA AND SOURCE DATA SET

The target area set in this study covers around 10,000 km x 6,700 km of 0-60 degree north for latitude direction and 60-150 degree east for longitude direction as shown in Figure 1a. The target region is covered by 51 sinusoidal projection grids which are distribution granule of SR（MYD09A1.5 Surface Reflectance 8-Day L3）and NBAR（MCD43A4.5 Nadir BRDF-Adjusted Reflectance 16-Day L3）products as shown in Figure 1b.



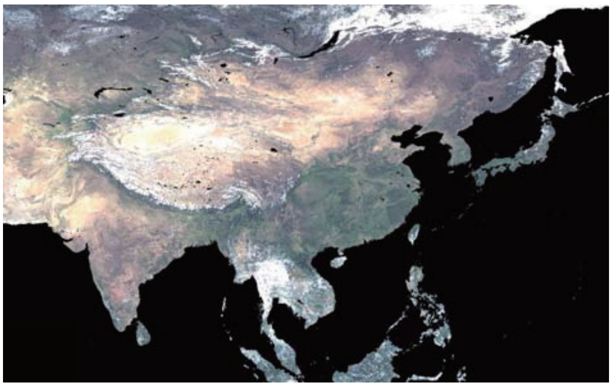
a. Target Region.



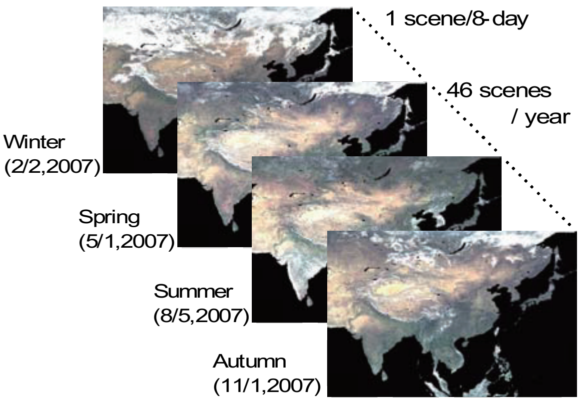
b. 51 sinusoidal projection grids.

Figure 1. Target area and MODIS products covered the region.

The SR and NBAR products of 51 sinusoidal projection grids were mosaicked and transformed to geographic longitude-latitude coordinate system as shown in Figure 2. This processing was performed by using MODIS Reprojection Tool（MRT）which has been distributed from Land Processes DAAC. Because SR and NBAR products have been produced in eight-day period, mosaic images of 46 scenes were generated as classification target data set for one year of 2007（in Figure 2b）.



a. a result image of mosaic and geometric transform



b. 46 scenes data of 2007

Figure 2. Classification target data set for one year of 2007.

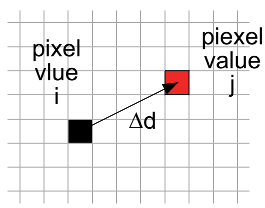
3. CLASSIFICATION ALGORITHM

3.1 Classification Feature

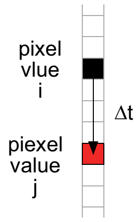
In this study, time-domain co-occurrence matrix was used as a classification feature which provides time-series signature of land covers. Each elements （i,j） of the time-domain co-occurrence matrix is defined as probability that two pixels with a specified time-separation Δt in the same spatial position have pixel value i and j（Figure 3）. Conventional co-occurrence matrix（spatial domain co-occurrence matrix） represents spatial texture while the proposed co-occurrence matrix represents time-series signature.

Figure 4a shows pixel values of annual time-series data conceptual. The time-domain co-occurrence matrices shown in Figure 4b are derived from this time-series data in the case of one month separation. That is, a time-series changing pattern of pixel values produces the corresponding probability distribution pattern in the matrix. Time-domain co-occurrence matrix takes advantage of robustness against data loss and noise derived from cloud and undesirable fluctuation of calculated reflectance values.

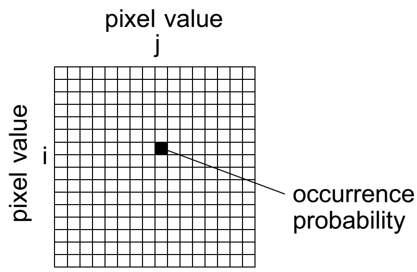
In our experiments, two kinds of pixel value were examined. The first one is surface reflectance. The second one is spectral cluster that is extracted by clustering in seven spectral bands for 46 scenes data set. It is expected that spectral clusters absorb undesirable fluctuation of surface reflectance. And time separation Δt from one to six months were examined in order to search proper Δt.



a. definition in spatial domain

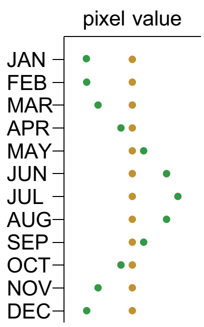


b. definition in time-domain

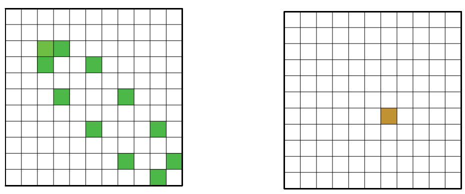


c. co-occurrence matrix

Figure 3. Co-occurrence matrix definition in spatial domain and time domain.



a. annual time-series



b. time-domain co-occurrence matrix

Figure 4. Conceptual examples of time-domain co-occurrence matrix.

3.2 Classifier and Land Cover Category

The non-parametric minimum distance classifier was conducted for time-domain co-occurrence matrix. Euclidean distance $d_E(x,c)$ and cosine distance $d_n(x,c)$ between a pixel-x and a class-c were examined in this experiments. The distance $d_E(x,c)$ and $d_n(x,c)$ are defined as Eq.(1) and Eq.(2), respectively.

$$d_E(x,c)=\sum_{b=1}^{7}\sum_{i}\sum_{j}\{M_{x,b}(i,j)-M_{c,b}(i,j)\}^2 \qquad (1)$$

$$d_n(x,c)=\frac{\sum_{b=1}^{7}\sum_{i}\sum_{j}M_{x,b}(i,j)M_{c,b}(i,j)}{\sqrt{\sum_{b=1}^{7}\sum_{i}\sum_{j}M^2_{x,b}(i,j)\cdot\sum_{b=1}^{7}\sum_{i}\sum_{j}M^2_{c,b}(i,j)}} \qquad (2)$$

When surface reflectance is utilized as pixel value of time-domain co-occurrence matrix, $M_{x,b}(i,j)$ is a component (i,j) of the time-domain co-occurrence matrix measured from band-b in time-series data set for a pixel-x. $M_{c,b}(i,j)$ is that measured from band-b time-series data set for the training area of a class-c. When spectral cluster is utilized as pixel value of time-domain co-occurrence matrix, band-b is the single channel that contains cluster ID.

Table 1 presents the land cover categories which are same with IGBP Land cover categories. These 17 categories were used in our classification experiments.

Table 1. Land cover categories (IGBP legend).

1. Water	
2. Evergreen Needleleaf Forest	
3. Evergreen Broadleaf Forest	
4. Deciduous Need leaf Forest	
5. Deciduous Broadleaf Forest	
6. Mixed Forests	
7. Closed Shrublands	
8. Open Shrublands	
9. Woody Savannas	
10. Savannas	
11. Grasslands	
12. Permanent Wetlands	
13. Croplands	
14. Urban and built-up	
15. Cropland/Natural Vegetation Mosaic	
16. Permanent snow and ice	
17. Barren/Sparsely vegetated	

4. CLASSIFICATION RESULTS

Forty classification classes were prepared for IGBP 17 categories, because each category consists of several classification classes. About 9,000 pixels on the average for each class and about 400,000 pixels in total have been extracted as training data. Classification accuracies were measured by using test samples of 500 pixels that were sampled randomly from training area of each individual class.

The cosine distance classifier has always produced mean producer's classification accuracy that is about 1% higher from the Euclidean distance classifier regardless of the time-separation Δt, as shown in Figure 5.

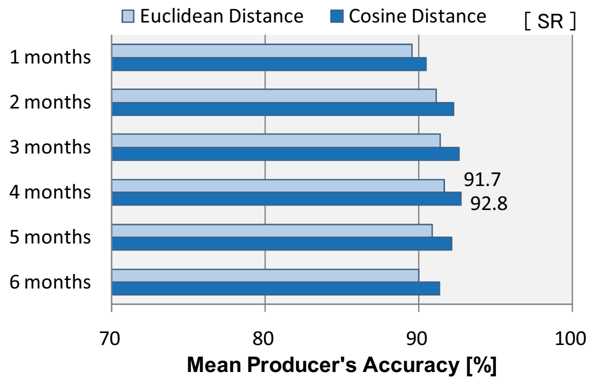


Figure 5. Comparison between Euclidean distance and cosine distance.

The cosine distance classifier using time-domain co-occurrence matrix defined by reflectance has produced mean producer's classification accuracy shown in Figure 6. In the utilizing case of surface reflectance (Figure 6), the highest accuracy of about 93% has been obtained for SR and NBAR products when time-separation Δt is 4 months. "M*D12Q1" indicated in Figure 6 means MOD12Q1 and MCD12Q1 of MODIS land cover product which are produced from SR and NBAR products, respectively. Accuracies of M*12Q1 product are about 10%-20% lower than those of our classification results.

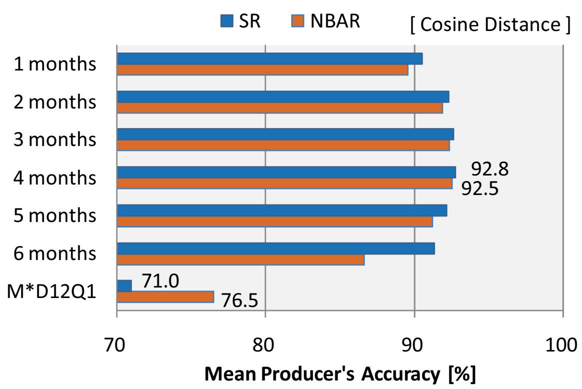


Figure 6. Classification accuracies obtained by time-domain co-occurrence matrix defined by reflectance.

Classification accuracies of M*D12Q1 were measured by using same test samples. Because test samples were extracted from training area for classification of SR and NBAR products, it is fundamentally presumed that the accuracy of MOD12Q1 and MCD12Q1 products is lower than that of SR and NBAR products. However, we consider that these classification accuracies of SR and NBAR products showed good performance of the proposed simple classification method.

Furthermore, the cosine distance classifier using time-domain co-occurrence matrix defined by spectral clusters of 2,000 has produced mean producer's classification accuracy shown in Figure 7. In the utilizing case of spectral clusters（Figure 7）, the highest accuracy of about 95% has been obtained for SR and NBAR product when time-separation Δt is 4 and 5 months. The accuracy is about 15%-20% higher than that of MODIS land cover products.

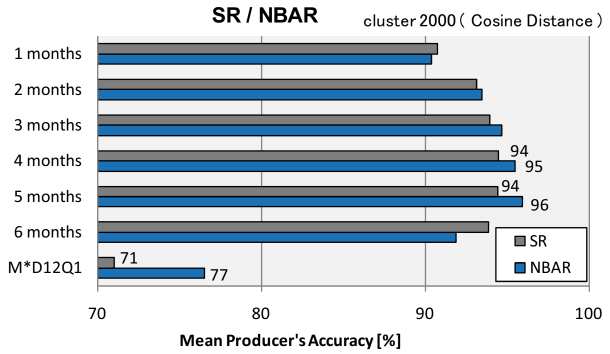
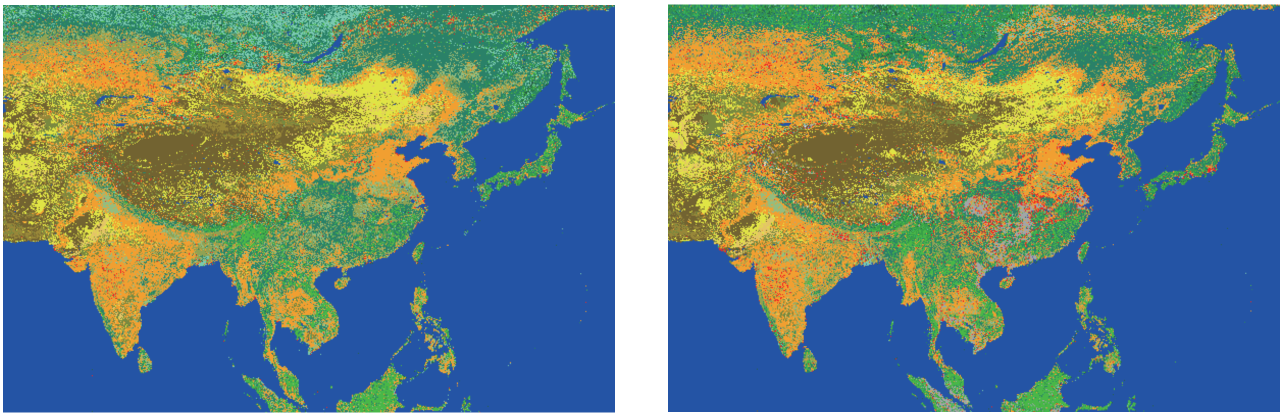


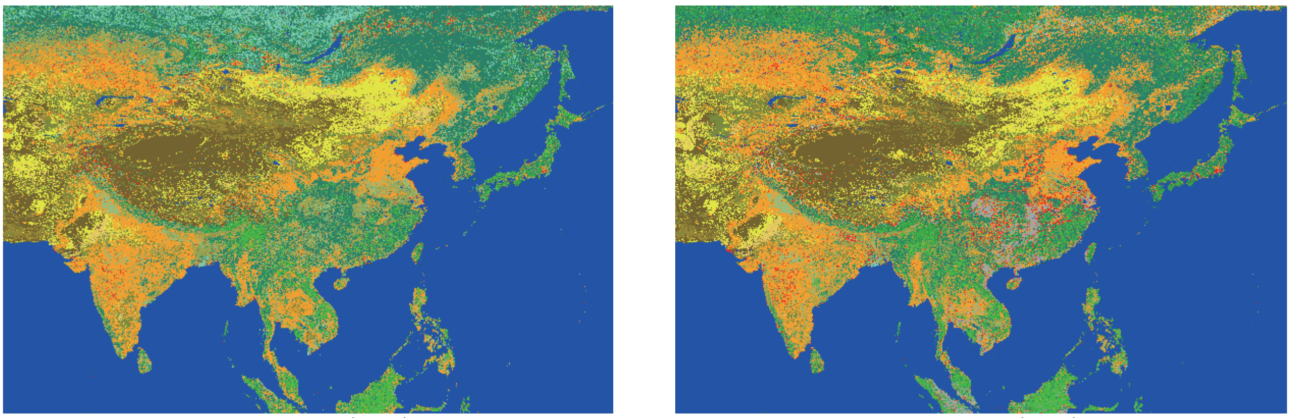
Figure 7. Classification accuracies obtained by time-domain co-occurrence matrix defined by spectral clusters（2000 clusters）.

Figure 8 and Figure 9 show classification results obtained by cosine distance classifier, when time-domain co-occurrence matrix is defined by surface reflectance and spectral cluster, respectively. And Figure 10 shows MYD12Q1（2004） and MCD12Q1（2007） MODIS land cover product.



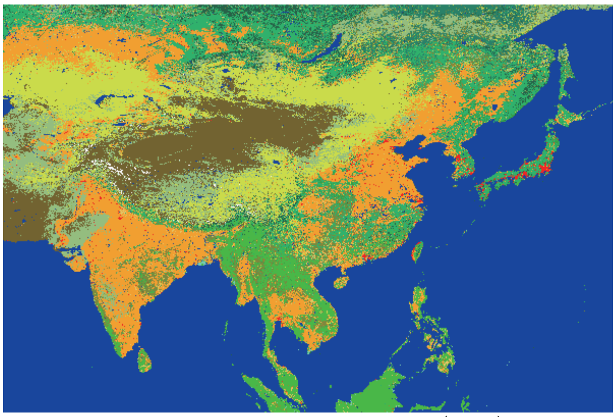
a. SR product（2007） b. NBAR product（2007）

Figure 8. Land cover classification results obtained by cosine distance classifier using the time-domain co-occurrence matrix defined by surface reflectance and four months time-separation.

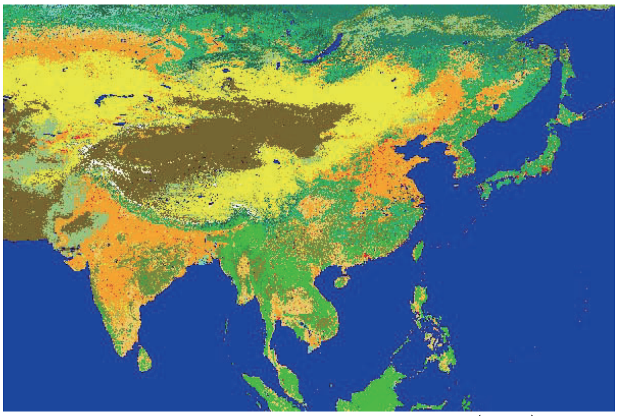


c. SR product（2007） d. NBAR product（2007）

Figure 9. Land cover classification results obtained by cosine distance classifier using the time-domain co-occurrence matrix defined by spectral clusters and five months time-separation.



e. MOD12Q1 land cover product（2004）



f. MCD12Q1 MODIS land cover product（2007）

Figure 10 MODIS land cover product.

5. CONCLUSIONS

Land cover classification for eastern Asia were performed by using multi-temporal MODIS reflectance products. The proposed method using the time-domain co-occurrence matrix and the non-parametric minimum distance classifier showed good classification performance compared with MOD12Q1 and MCD12Q1 MODIS land cover product. Especially, the highest classification accuracy was obtained when the non-parametric cosine distance classifier was driven by the time-domain co-occurrence matrix defined by spectral clusters and four or five months time-separation. And also, it was cleared that Surface Reflectance 8-Day L3 product and Nadir BRDF-Adjusted Reflectance product showed similar classification accuracy of 92%-96% for IGBP-17 land cover categories. Future study should be carry out in our classification scheme in order to expand classification target area and to validate classification accuracy with more suitable test samples.

Acknowledgements

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