# GLOBAL LAND COVER CLASSIFICATION USING MODIS SURFACE REFLECTANCE PRODUCTS

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**KEY WORDS:** Land Cover, Classification, Global, MODIS

**ABSTRACT:** The objective of this study is to develop land cover classification algorithm for global scale 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, time-domain co-occurrence matrix was introduced as a classification feature which provides time-series signature of land covers. And non-parametric minimum distance classification was conducted. As results, Surface Reflectance 8-Day L3 product and Nadir BRDF-Adjusted Reflectance product showed similar classification accuracy of 91%-93% for IGBP-17 land cover categories. Furthermore, it is confirmed that the classification accuracy is 14%-17% higher than that of MODIS land cover product.

## 1. INTRODUCTION

Land cover maps of global or continental scale are basic information for many kinds of applications, i.e. global change research, modeling, resource management, etc. The objective of this study is to develop land cover classification algorithm for global/continental scale 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 140° (from 70° north to -70° south) and 360° for latitude and longitude direction, respectively. The region is covered by about 280 sinusoidal projection(SIN) grids which are distribution granule of SR and NBAR products (as shown in Figure 1). The SR and NBAR products of about 280 SIN grids were mosaicked and transformed to geographic longitude-latitude coordinate system with 0.005 degree interval 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.

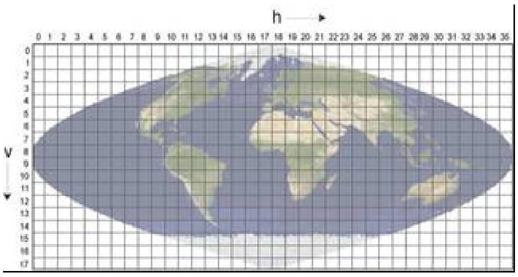



Fig. 1 SIN grid.

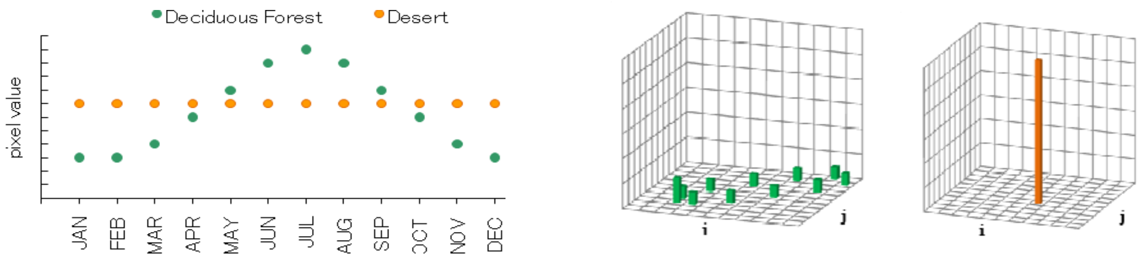
Fig. 2 A result of mosaic and geometric transform. (the scene of 2007.01.01)

## 3. PROPOSED CLASSIFICATION ALGORITHM

### 3.1 Classification Feature

In this study, time-domain co-occurrence matrix was introduced 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 delta-t in the same spatial position have pixel value i and j. Conventional co-occurrence matrix(that is spatial domain co-occurrence matrix) represents spatial texture while the proposed time-domain co-occurrence matrix represents time-series signature.

Figure 3a shows pixel values of annual time-series data conceptual. The time-domain co-occurrence matrices shown in Figure 3b 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.




(a) annual time-series (b) time-domain co-occurrence matrices

Fig. 3 Conceptual examples of time-domain co-occurrence matrix.

### 3.2 Classifier

The non-parametric minimum distance classifier was introduced 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 training 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.

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

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

$M_{x,b}(i,j)$ 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.

## 4. CLASSIFICATION EXPERIMENTS

### 4.1 Land Cover Category

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

### 4.2 Training and Accuracy Estimation

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. Figure 4 and Figure 5 show examples of training data for "evergreen needleleaf forest" and " barren/sparsely vegetated", respectively. Figure 6 shows examples of obtained time-domain co-occurrence matrix for "deciduous needleaf forest" and " savannas".

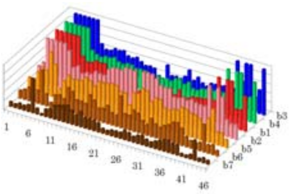
Classification accuracies were measured by using test samples of 500 pixels that were sampled randomly from training area of each individual class.

Table 1. Land cover categories(IGBP legend).

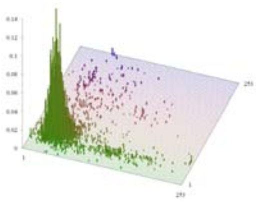
| | |
|---|---|
| 1. Water | |
| 2. Evergreen Needleleaf Forest | |
| 3. Evergreen Broadleaf Forest | |
| 4. Deciduous Need leaf Forest | |
| 5. Deciduous Broadleaf Forest | |
| 6. Mixed Forests | |
| 7. Closed Shrublands | |
| 8. Open Shrublands | |
| 9. Woody Savannas | |
| 10. Savannas | |
| 11. Grasslands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

(a) ground view

(b) training area



(c)time series reflectance of one pixel in the training area

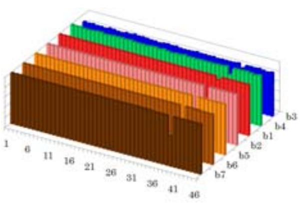


(d)time-domain co-occurrence matrix of the training area

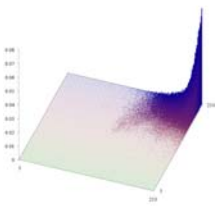
Fig. 4 Training data example for "evergreen needleleaf forest".

(a) ground view

(b) training area

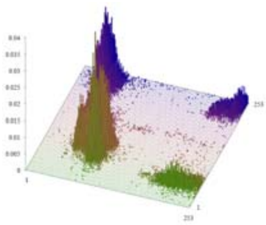


(c) time series reflectance of one pixel in the training area

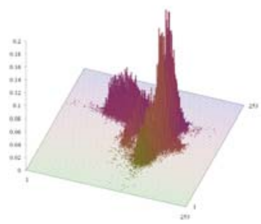


(d)time-domain co-occurrence matrix of the training area

Fig. 5 Training data example for "barren/sparsely vegetated".



(a) "deciduous needleaf forest"



(b)"savannas"

Fig. 6 Examples of obtained time-domain co-occurrence matrix.

### 4.3 Results

The cosine distance classifier has always produced mean producer's classification accuracy that is several percent higher than the Euclidean distance classifier regardless of the time-separation delta-t. Figure 7 shows obtained mean produce's accuracy of the cosine distance classifier. the highest mean producer's classification accuracy of 91% and 93% have been obtained for SR and NBAR products when time-separation delta-t are 3 and 4 months, respectively.

"M?D12Q1" indicated in Figure 7 means MOD12Q1 and MCD12Q1 of MODIS land cover product which are produced from SR and NBAR products, respectively. Accuracies of M?12Q1 product are 7%-14% lower than those of our classification results. 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 our classification results. However, we consider that these classification accuracies of SR and NBAR products showed good performance of the proposed simple classification method.

Figure 8 shows the classification results obtained by cosine distance classifier in the case of the highest accuracy

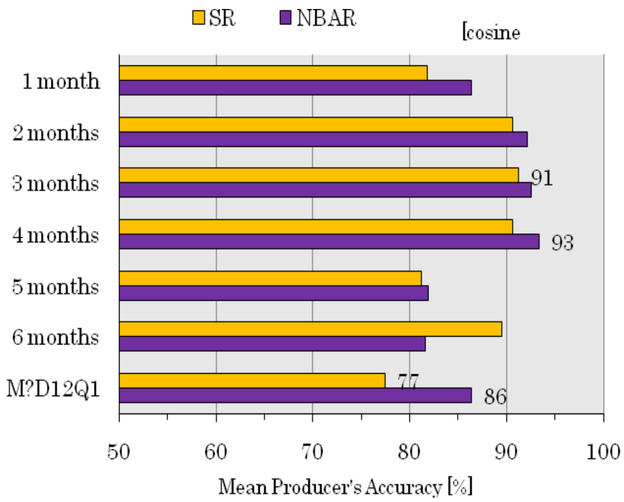
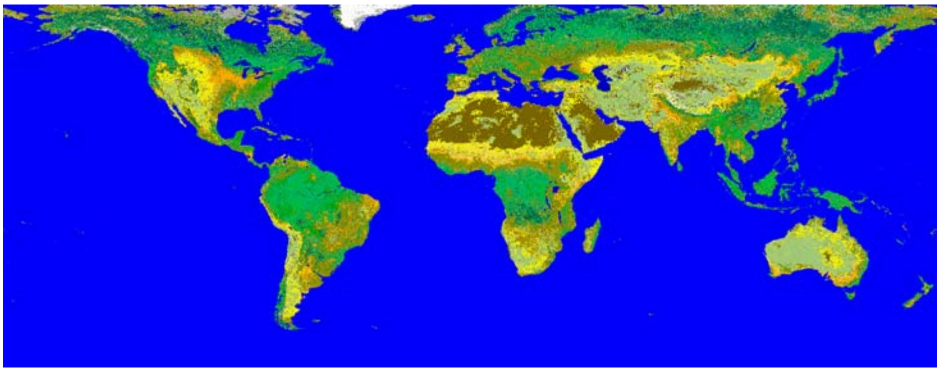
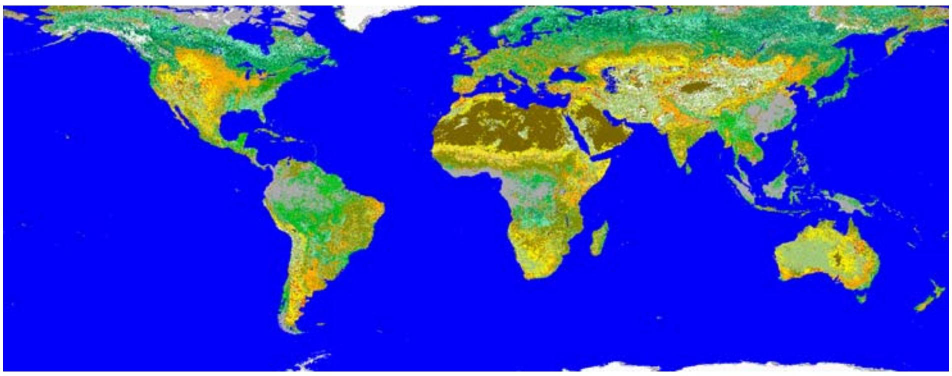



Fig. 7 Classification accuracy.



(a) SR product (2007)



(b) NBAR product (2007)

Fig. 8 Land cover classification results.

## 4. CONCLUSIONS

Land cover classification for global/continental scale were performed by using two kinds of 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 three 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 91%-93% for IGBP-17 land cover categories.

Future study should be carry out in our classification scheme in order to examine stability of classification for multiple years and to validate classification accuracy with more suitable test samples.

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