

**EASTERN ASIA LAND COVER CLASSIFICATION USING MODIS SURFACE REFLECTANCE PRODUCTS**

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**KEYWORDS:** Land Cover, Classification, MODIS, Surface Reflectance, Co-occurrence Matrix, Minimum Distance Classifier.

**ABSTRACT:**

The objective of this study is to develop land cover classification algorithm suited for 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. As results, Nadir BRDF-Adjusted Reflectance product showed higher classification accuracy than Surface Reflectance 8-Day L3 product. Furthermore, those products produced good land cover maps than MODIS land cover product for the target classification area.

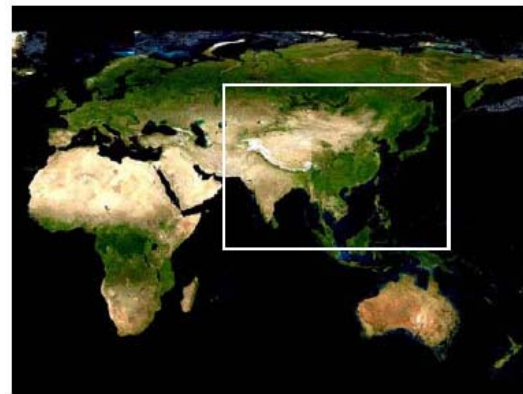
**1. INTRODUCTION**

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. NDVI or similar indexes are generated by only 2 or 3 channels and in addition they lose the brightness information. 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.

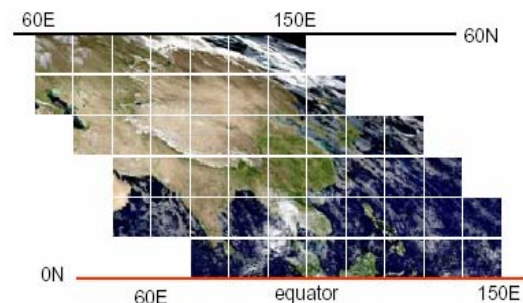
**2. STUDY AREA AND SOURCE DATA SET**

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. 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).

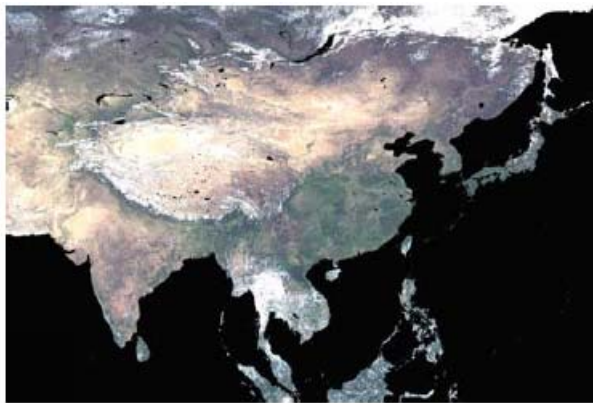


a. Target Region.

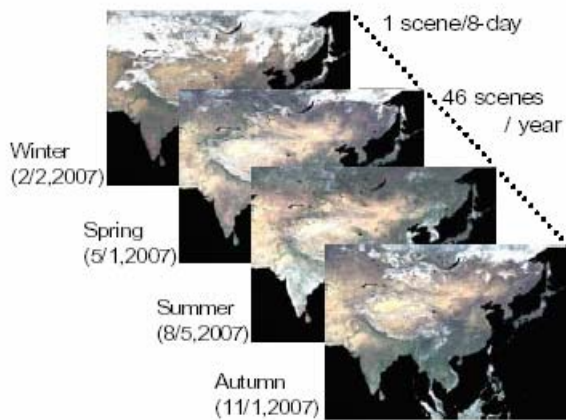


b. 51 sinusoidal projection grids.

Figure 1. Target area and MODIS Products Covered the Region



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

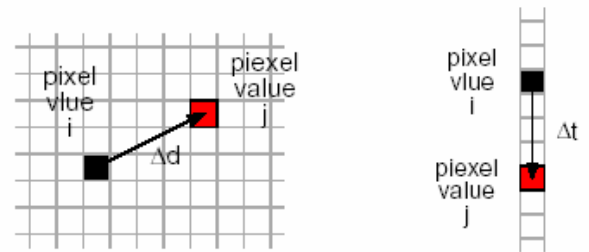
### 3. CLASSIFICATION ALGORITHM

#### 3.1 Classification Feature

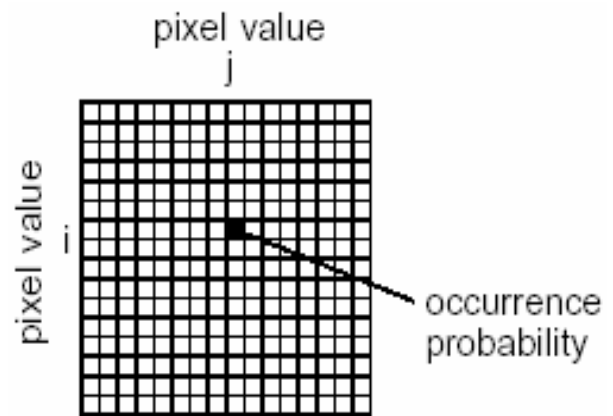
In this study, time-domain co-occurrence matrix was used as a classification feature, which provides time-series signature of land covers. Each elements  $(i, j)$  of the time-domain co-occurrence matrix is defined as probability that two pixels with a specified time-separation  $\Delta t$  in the same spatial position have pixel value  $i$  and  $j$ . 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. Two, four and six months as time-separation  $\Delta t$  were examined in this experiment.

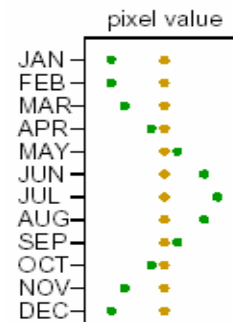


a. Definition in Spatial Domain b. Definition in Time-Domain

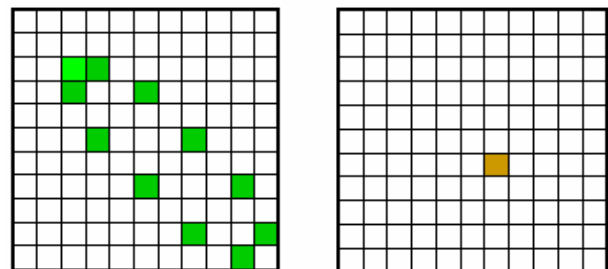


c. co-occurrence matrix

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 Classes**

The 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.

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

$$d_n(x,c) = \frac{\sum_{b=1}^7 \sum_i \sum_j M_{x,b}(i,j) M_{c,b}(i,j)}{\sqrt{\sum_{b=1}^7 \sum_i \sum_j M_{x,b}^2(i,j) \cdot \sum_{b=1}^7 \sum_i \sum_j M_{c,b}^2(i,j)}} \quad (2)$$

$M_{x,b}(i,j)$  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- $c$ . Table 1 presents the land cover classes, which are same with IGBP Land cover classes.
















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	

Table 1. Land Cover Classes (IGBP legend)

**4. CLASSIFICATION RESULTS**

Table 2 shows the classification accuracy of category maps obtained by our classification experiment. Classification accuracies were measured by using test samples of 500 to 5000 pixels that were sampled randomly from training area of each individual class.

In Table 2, overall accuracy means the percentage of samples correctly classified among a total test samples. Mean producer's accuracy means the category mean of percentage of samples correctly classified among test samples belonging to a land cover category. And, mean user's accuracy means the category mean of percentage of correct samples among test samples classified to a land cover category. MOD12Q1 and MCD12Q1 of MODIS land cover product are produced by using SR products and NBAR products, respectively. Proposed methods using four month time-separation and Euclidian distance show good performance. In that case, NBAR products indicated 93% overall accuracy, 91% mean producer's accuracy, and 92% mean user's accuracy. SR products indicated a little lower accuracy than those values. Furthermore, these accuracies; especially mean producer's and user's accuracy, are higher than that of MOD12Q1(2005) and MCD12Q1(2007) products. Because test pixels 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 this classification results showed good performance of the proposed simple classification method.

source product	$\Delta t$ month	dist.	overall accuracy	M.P. accuracy	M.U. accuracy
SR	MOD12Q1		89 %	71 %	43 %
	2	Euc. cos.	91 % 74 %	90 % 71 %	89 % 81 %
	4	Euc. cos.	92 % 77 %	91 % 73 %	90 % 82 %
	6	Euc. cos.	91 % 75 %	90 % 70 %	90 % 83 %
NBAR	MCD12Q1		91 %	76 %	41 %
	2	Euc. cos.	92 % 86 %	91 % 82 %	91 % 89 %
	4	Euc. cos.	93 % 87 %	91 % 85 %	92 % 90 %
	6	Euc. cos.	90 % 84 %	89 % 82 %	89 % 87 %

Table 2. Classification accuracy. (M.P.:mean producer's, M.U.:mean user's)

Figure 5a and Figure 5b show the classification results of SR product and NBAR products when two months time-separation and Euclidian distance were used. And Fig. 5c shows MCD12Q1 MODIS land cover product. Target area and Kanto region including Tokyo are represented in Figure 5, respectively.

**CONCLUSION**

Land cover classification were performed by using multi-temporal MODIS reflectance products. The proposed time-domain co-occurrence matrix showed good classification performance compared with MOD12Q1 and MCD12Q1 MODIS land cover product. Especially, the highest classification accuracy was obtained when the minimum distance classifier using Euclidean distance was driven by the time-domain co-occurrence matrix defined by four months time-separation. And also, it was cleared that Nadir BRDF-Adjusted Reflectance 16-Day L3 product shows a little higher classification accuracy than Surface Reflectance 8-

Day L3 product. Future study should be carry out in our classification scheme in order to increase the classification accuracy and to obtain more stable results.

#### **ACKNOWLEDGEMENTS**

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