

# UNDERSTANDING LAND-COVER CHANGE PATTERNS USING MULTI-TEMPORAL MODIS DATA IN WEST JAVA, INDONESIA

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**KEYWORDS:** Land-cover change, multi-temporal MODIS data, Enhanced Vegetation Index (EVI), Wavelet transformation, West Java

## ABSTRACT

Land-use land-cover (LULC) changes are globally issues that significantly affect key aspects of the human-environment system. The conversion of forested and other undeveloped land to developed, urban areas are often considered to be a cause of increasing landslides, erosion and flood frequency and magnitude as well as local climate change in many sites of West Java.

Important data on the rate and spatial distribution of LULC changes have been provided by the analysis of remote sensing images, unfortunately, identification of such changes by remote sensing faced difficulties while landscapes are complex with mixing of different types of land cover condition and also make difficult to distinguish between temporary and permanent land cover changes.

In this study a spatial approach is designed to analyze the transition pattern of land-cover changes of West Java, based on an extensive analysis of land-cover change from data sets of multi-temporal MODIS Vegetation Indices products. Such analysis examined the changes of surface condition by using image differencing technique. The signal filtering process "Wavelet transformation" also has been applied to remove corrupted (noise) data values of the MODIS VI.

This study showed that high temporal resolution of the MODIS EVI 250 m data has significant advantage for both capturing the actual timing of the change event and the subsequent monitoring of the recovery to the next stage, however, such changes are limited by spatial resolution of data.

## 1 INTRODUCTION

Recently, there is increased recognition that land-use change is a major driver of global change, through its interaction with climate, ecosystem processes, biogeochemical cycle, biodiversity and human activities (IGBP-IHDP, 1999). At a global scale, land-use changes are cumulatively transforming land-cover at an accelerating rate (Turner *et al.*, 1994). Related to such global issues, monitoring of spatial distribution of land-use land-cover (LULC) changes can be provided by the analysis of remote sensing images, unfortunately, identification of such changes by remote sensing have been facing difficulties due to landscapes complexity with regard to mixing of different types of land cover condition.

One of the difficulties in land-cover change analysis have been recognized related to dry and wet season as well as rice field (planted) and rice field (unplanted) related to growing season. Such "temporary" land-cover changes are addressed to phenological dynamics of terrestrial ecosystems reflects response of the Earth's biosphere to annual dynamics of the Earth's climate and hydrologic (Zhang *et al.*, 2003) and biologically complex ecosystems (Lunetta *et al.*, 2006). We considered that each land-cover will illustrate different "phenology" (temporal changes) pattern in certain time range, and it can be used to detect the changes among them.

Land-cover change detection using multi-temporal MODIS NDVI data has been investigated by Lunetta *et al.* (2006). They have applied a discrete Fourier transformation technique to filter and remove

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Paper presented in Geoinformation Forum 2009, 17-19 June 2009, Pacifico Yokohama, Japan. Japan Association of Surveyors (JAS). Japan

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corrupted data values of MODIS NDVI data. The methods and results applied only to non-agricultural areas. However their result showed the overestimation of change area whereas attributed to the coarse resolution of the NDVI data, but high temporal resolution of the MODIS NDVI 250 m data has significant advantage for both capturing the actual timing of the change event and the subsequent monitoring of the recovery to the next steady state.

The objective of this study is to investigate and analyze the transition pattern of land-cover and to detect the LULC changes in West Java using multi-temporal image data. The consideration of such transition pattern will assist further research in understanding the dominant process of land-use change allocation and to take it into consideration when land-use change model are made.

## 2 METHODOLOGY

### 2.1 Datasets and data preparation

#### 2.1.1 Satellite data

In this study we used MODIS product name “MODIS Terra Vegetation Indices (VI) 16-day L3 Global 250m SIN Grid V005 (MOD13Q1)” were acquired between January 2001 and December 2002. They were obtained freely from Land Processes Distributed Active Archive Center (LP DAAC), U.S. Geological Survey (<http://lpdaac.usgs.gov/datapool/datapool.asp>). This VI product contains two indices, that is: the Normalized Difference Vegetation Index (NDVI) and a new Enhanced Vegetation Index (EVI).

#### 2.1.2 Corresponding land-use datasets

The information of land-use map in West Java was obtained from Department of Forestry (DoF) in 2000 and Ministry of the Environment (MoE) in 2003. Such data sets are used as reference in order to evaluate the EVI time-series derived from MODIS data. Both of data sets have different number of land-use class, the DoF classified into 22 types and the MoE 12 types.

Therefore, we synchronized with the same definition, considering our objective and area of study. Thus, we reclassified such land-use data sets into 10 categories, as follows forest, paddy field (consists of 3 classes), upland, upland mixed bush, mixed garden, timber plantation, non timber plantation, bush mixed garden, bare-land, and built up (settlement).

### 2.2 Filtering the time-series EVI profile by Wavelet transformation

Time-series EVI data obtained by satellite include various noise components such as aerosols and bidirectional reflectance distribution factors (Sakamoto, et.al., 2005). So as to reduce such kind of noise, several studies have filtered observed data due to linear interpolation (Viovy *et al.*, 1992), Principal Component Analysis (Li & Kafatos, 2000), Fourier transform (Azzali & Menenti, 2000) and Wavelet transform (Sakamoto *et al.*, 2005). Because of the Wavelet transform can be used to remove noise and identify the timing of events such as localized objective signals in the presence of noise, as mentioned by Sakamoto et.al (2005), in this study we employed such transform method to filter our time-series EVI data.

The Wavelet transform used is functioned as follows:

$$Wf(a, b) = \int_{-\infty}^{+\infty} f(x) \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right) dx$$

where  $a$  is a scaling parameter,  $b$  is a shifting parameter, and  $\psi$  means a mother wavelet.

In this study, the wavelet analysis used the *coiflet* 4 wavelet function that was performed with MATLAB (The MathWorks, Inc.)

### 2.3 Clustering for land-cover categories

In order to simplify the representation of EVI MODIS pattern, and also easier to analyze, we applied

segmentation process through clustering method. We used the ascending hierarchical method with Euclidean distance to evaluate the variation of EVI MODIS pattern. The clustering method results a number of significant land-cover pattern that correspond to such kind of land-cover type. Referring to that information, we applied supervised classification with employ those land-cover patterns as signature sample. Besides, based on such pattern also we detected the LULC change area.

## 2.4 Approach for analyze land-cover change

### 2.4.1 Land-cover pattern interpretation

The EVI can be linearly correlated with the leaf area index and more sensitive than NDVI in high biomass areas (Huete *et al.*, 2002). Moreover, Zhan *et al.* (2000) explain that the EVI data provide information on characteristics of the vegetation such as seasonality, in which calculated as the amplitude of the EVI temporal profile.

Therefore, we applied such temporal profile to classify land-cover types and to analyze its changes. The other image satellite data in similar acquisition time (e.g. Landsat data) also have been used to identify those patterns. The fluctuation of EVI value was addressed to changes of land-cover, either temporal or permanent of changes, whereas the areas with low EVI indicates less vegetation and vice versa.

### 2.4.2 Finding optimal threshold values for change detection

In our study, threshold values are set to equal distances from the mean of EVI value ( $2 \times$  standard deviation). We assume that the difference EVI usually yields an EVI distribution which is approximately normal (Gaussian) in nature, where pixels of no EVI change are distributed around the mean and pixels of changes are found in the tails of the distribution. The research flowchart for understanding the land-cover change pattern is shown in Fig.1.

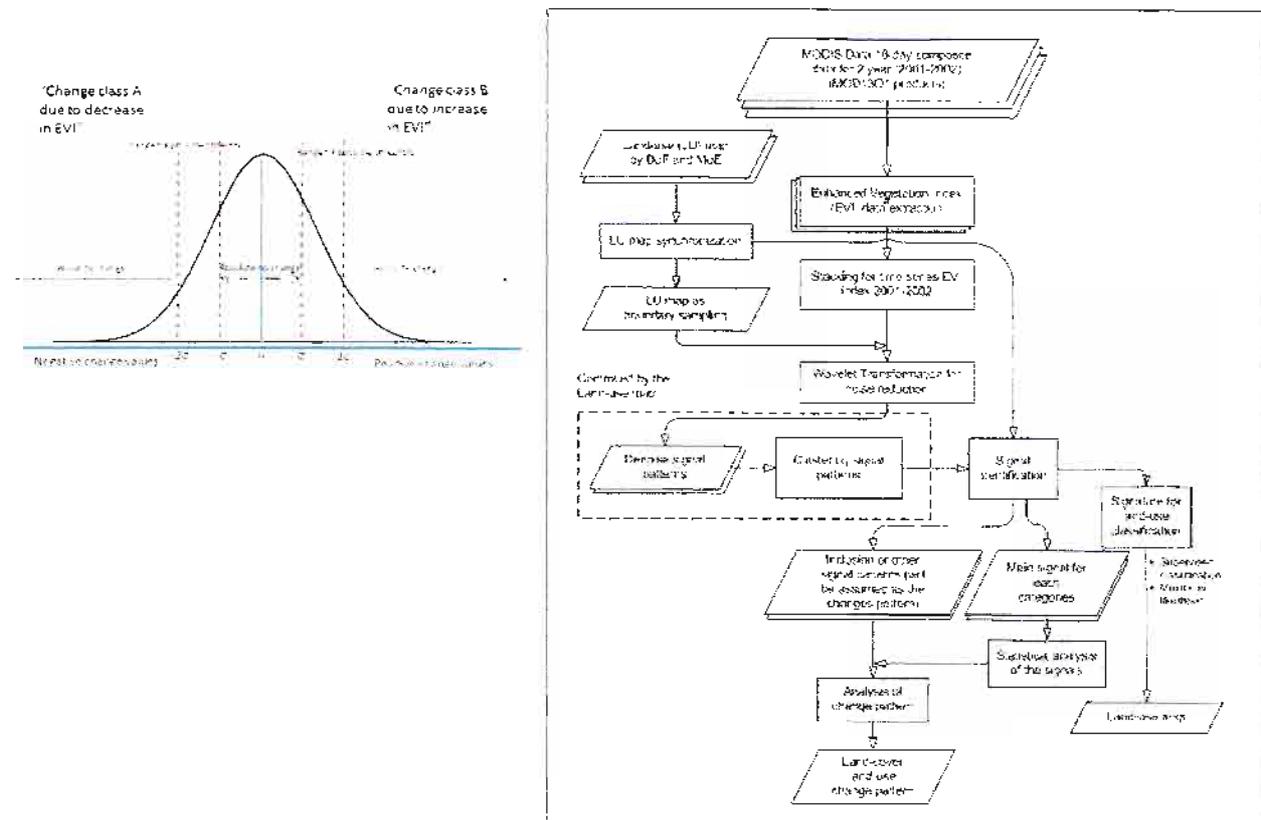


Fig.1.(a) Hypothetical EVI distribution of pixels in the difference image. The hypothetical high and low-end threshold values are set at  $\pm 2$  standard deviations from mean for change pixels. (b) Research flowchart for understanding the land-cover change patterns in this study

### 3 RESULTS AND DISCUSSION

#### 3.1 Land-cover pattern analysis

As stated above that each land cover type showed different temporal change pattern of EVI, moreover, we have identified the type of land cover precisely by those patterns. The result of analysis pattern for 2001 and 2002 are presented in Fig.2.

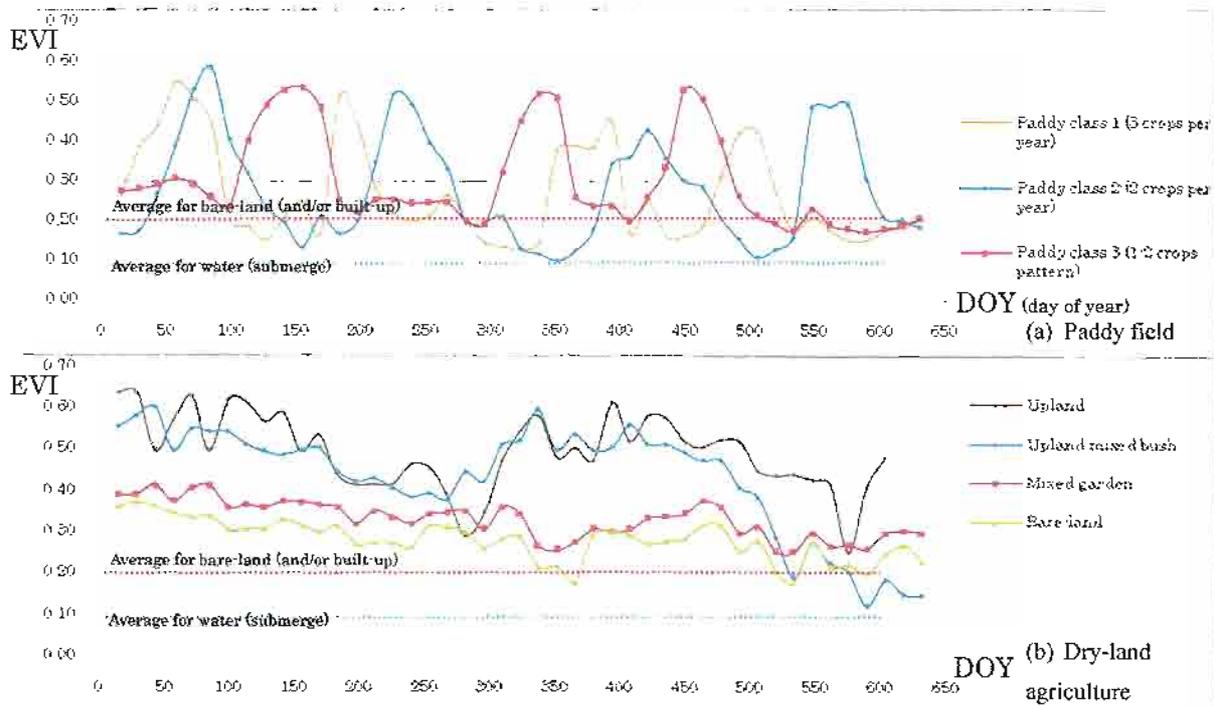


Fig.2. MODIS EVI temporal pattern of agriculture land from 2001 to 2002 (a) paddy field, (b) dry-land agriculture

Fig.2. indicates the evident maximum of EVI at the time of transplanting and sharp decreasing after the event, except for mixed garden and bare-land. Seasonal pattern of land cover can be understood obviously from those patterns, especially agricultural cropping system such as: paddy field and upland, and also many events among them. When transplanting stage, paddy field area is submerged and then vegetative activity starts to emerge.

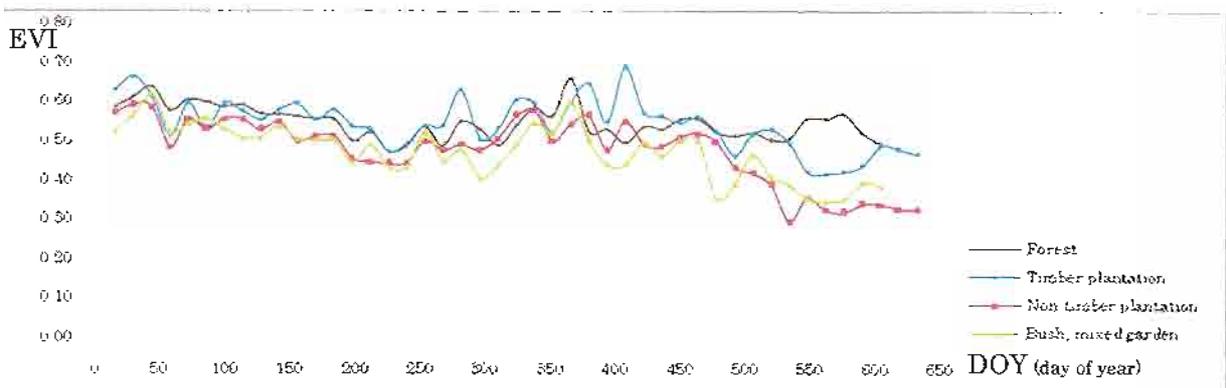


Fig.3. MODIS EVI temporal pattern of non-agriculture land from 2001 to 2002

In addition, the application of temporal pattern for generate land-use map is illustrated in Fig.4. It is noted that even for the area with complex cropping pattern MODIS data might extract the growing phase of

vegetation if appropriate method of estimation was developed.

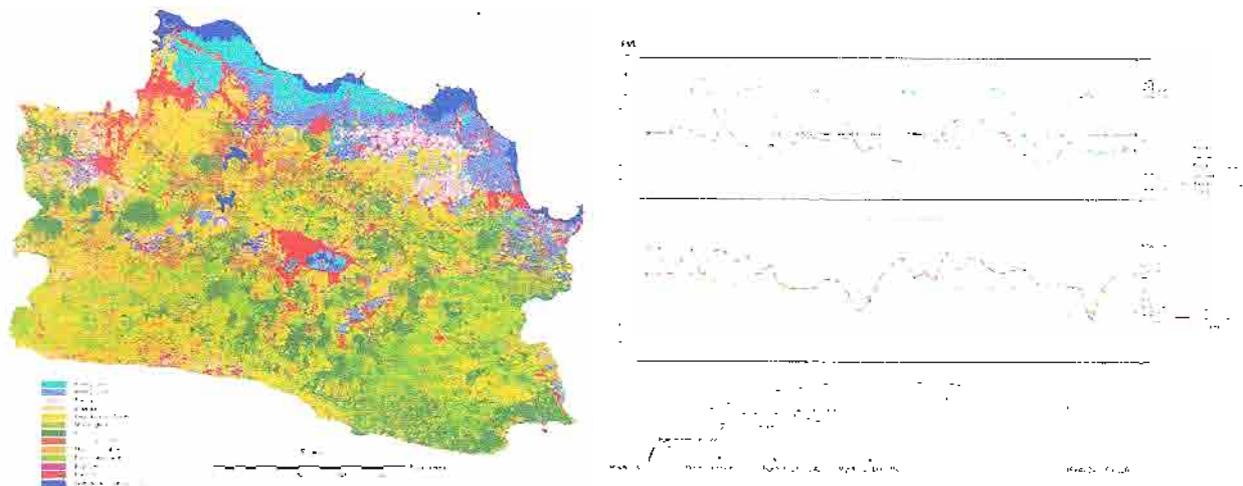


Fig.4. (a) Land-use map generated by temporal pattern of EVI, (b) Time interval over temporary changes in agricultural area, which can be detected by time-series MODIS data due to threshold level of SD

### 3.2 Land-cover and land-use change detection

The results of change detection due to a threshold level of standard deviation ( $2*SD$ ) are presented in Table 1. Table 1 illustrate the analysis pattern of land-cover can be used for monitoring conversion forest to non-forest (*deforestation*), and agricultural land to non-agricultural cover types. However, the using of threshold  $2.0*standard\ deviation$  can not detected land-cover land-use change from paddy field, because range of that threshold so many large.

As pointed out by Lunetta (2006) an important consideration in the application of the change detection procedure using threshold levels of standard deviation which have presented here is the sub-pixel sensitivity of the minimal detection limit associated with the approach.

Table 1. Change detection results correspond to a threshold level of  $2.0*standard\ deviation$  for each category

Land-cover/land-use category (Cover type)	A	B	C	D	E	F	G	H	I	J
	Change area (Km <sup>2</sup> )									
Forest	0.0	0.2	0.4	12.4	N	3.2	0.1	0.1	0.0	0.0
Bush, mixed garden, bare	0.0	0.1	0.3	6.6	0.0	N	0.1	0.0	0.4	0.0
Timber plantation	0.2	2.8	0.0	8.3	0.0	0.0	N	0.0	1.9	0.0
Non-timber plantation	0.6	1.7	4.8	0.1	0.0	4.6	0.3	N	1.7	0.0
Bare land	0.1	8.1	6.6	0.0	0.0	0.0	0.0	0.0	N	0.0
Paddy	N	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Upland, dryland	0.0	N	0	4.4	0.0	0.0	0.1	0.0	0.0	0.0
Upland mixed with bush	0.0	0.0	N	1.0	0.0	12.7	0.3	0.7	0.5	0.0
Mix garden	0.2	0.0	8.0	N	0.0	0.0	0.0	0.0	0.7	0.0

Note: (A) Paddy (B) Upland/dryland (C) Upland mixed with bush (D) Mix garden (E) Forest (F) Bush, mixed garden, bare (G) Timber plantation (H) Non-Timber plantation (I) Bare-land (J) Built-up/Settlement

### 3.3 Accuracy assessment

The detection land-cover land-use change due to pattern analysis was validated using land-use change map 2000-2003 by DoF and MoE. The validation result showed the overall accuracy and overall Kappa statistics of the approach is 59.97% and 0.378, respectively. Moreover, the producer accuracy and user accuracy of such changes for each land-use are presented in Table 2.

Table 2. Accuracy assessment of the change detection results

The changes area of	Reference Totals	Classified Totals	Producers Accuracy	Users Accuracy
Forest	25	50	96,00 %	48,00 %
Bush, mixed garden, bare	8	11	75,00 %	54,50 %
Timber plantation (non)	92	21	13,04 %	57,14 %
Bare land	63	11	11,11 %	63,64 %
Upland, dryland	285	403	87,02 %	61,54 %
Mix garden	134	94	50,00 %	71,28 %
Un-change	17	0	0	0

#### 4 CONCLUSION

This study showed that Wavelet transform can be applied to remove noise and detect the temporary changes of land-cover. Moreover, the using of high temporal resolution of the EVI 250 m data has significant advantage for both capturing the actual timing of the change event and the subsequent monitoring of the recovery to the next stage. However, the threshold levels of the land-cover land-use changes needed to be developed.

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