TEMPORAL PATTERN ANALYSIS OF WAVELET-FILTERED MODIS EVI TO DETECT LAND USE CHANGE IN JAVA ISLAND, INDONESIA

Y. Setiawan [a], K. Yoshino [b]

[a] Graduate School of Life and Environmental Sciences, University of Tsukuba,Tennoudai 1-1-1, Tsukuba, Ibaraki 305-8577, Japan – s1030334@u.tsukuba.ac.jp
[b] Graduate School of System and Information Engineering, University of Tsukuba,Tennoudai 1-1-1, Tsukuba, Ibaraki 305-8577, Japan – sky@sk.tsukuba.ac.jp

Commission VIII, Working Group VIII/8

KEY WORDS: Land use change, temporal patterns analysis, MODIS EVI, wavelet transform

ABSTRACT:

Recently, land use and cover change is recognized as a one of major drivers of global change. Consequently, an updated and accurate database concerning their distribution is essential for global change research. This study investigated a land use change based on change of temporal pattern which applied to the wavelet-filtered MODIS EVI from 2000 to 2009. The temporal pattern analysis was able to detect the actual timing of change event in Java, either by conversion or vegetation growth; however, such capability was limited on global scale analysis. We identified several types of significant change pattern; those have contributed into the land use change. Nevertheless, the change detection based on temporal pattern became complicated in several sites of agricultural land, since they were detected as a land use change, even if they were not. Such phenomena were affected by the climate pattern issues, e.g. El-Nino. The use of multi-temporal data sets will be necessary to develop methodologies that utilize information on inter-annual variations to increase the accuracy of the land surface characterization.

1. INTRODUCTION

Land use and cover change (LUCC) is recognized as a one of major drivers of global change, through its interaction with climate, ecosystem processes, biogeochemical cycle, biodiversity and human activities (Lambin et al., 1999).

At a landscape scale, the conversion either vegetated land into non-vegetated land or undeveloped land into urban area is often considered to be one cause of increasing landslide, erosion and either frequency or magnitude of flood. In Java, flooding and landslide take place almost every year in many sites. Land use change analysis in Java was investigated by Verburg et al. (1999). They concluded that land use change will especially occur in the lowland areas, either directly through construction or indirectly through the demand for higher value crops. In addition, Prasetyo et al. (2009) demonstrated the application of spatial modelling for forest conversion in Java. Furthermore, some research had studied LUCC at detailed subjects and scales by identifying the significantly impact on habitat distribution (Ardli and Wolff, 2009) and altering the hydrologic characteristics (Runtunuwu and Pawitan, 2007). All of these studies indicated the need to construct an updated and accurate database concerning the land use change in Java.

A key requirement for the accurate land use change analysis at the global scale is the ability to distinguish the actual and temporal changes of land cover. For example, some trajectories in the paddy fields, such as: paddy-bareland-secondary crops-bareland, paddy-bareland-inundated-paddy-bareland-secondary crops, and paddy-bareland-secondary crops-bareland-inundated-paddy, are repeated year after year following the seasons, eventually describing temporal patterns that are characteristic of the cropping systems in some regions of tropical area. In this example, attributes of the land surface are: vegetated, bareland, and inundated, which is defined as temporal changes of land cover. On the other hand, land use describes the purposes for which humans exploit that land, e.g, paddy field, upland and their conversion into settlement. Land use involves both the manner in which biophysical attributes of the land are manipulated and the intent underlying that manipulation, e.g, the purpose for which the land is used (Lambin and Geist, 2006). The same distinction is important when considering plantation crops, forest and other types, even if there is a difference in time scale of trajectory cycle.

DeFries and Townshend (1994) emphasized that multi-year data sets would improve the capability to ensure that a classification result and land use change analysis were not the product of short-term fluctuations in vegetative activity. The uses of multi-year data sets are necessary to develop methodologies that utilize information on inter-annual variations to increase the accuracy of the land surface characterization. Meanwhile, the use of moderate spatial-resolution (250 m pixels) of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on board Terra and Aqua Satellites have some advantages in providing basic information to recognize the temporal pattern of land surface.

* Corresponding author: Tel: +81-29-853-5577.
E-mail address: s103034@u.tsukuba.ac.jp (Y. Setiawan)

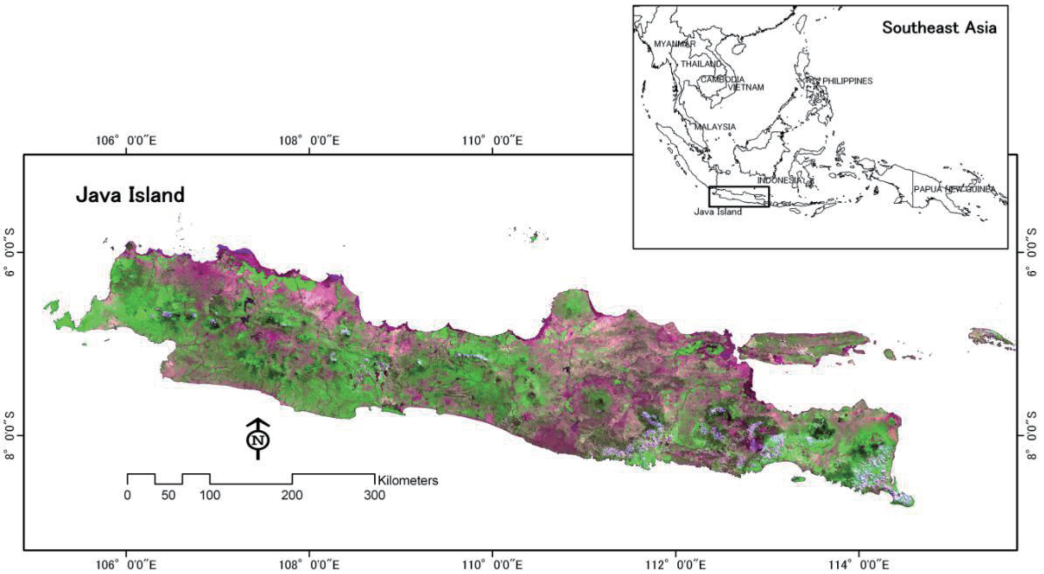


Figure 1. The study area

Moreover, to get a higher percentage of clear-sky data, the Maximum Value Composited (MVC) method is applied to the MODIS VI and is combined with the MODIS BRDF (Bidirectional Reflectance Distribution Function) or MOD43-product to generate the 16-day composite MODIS VI (MOD13Q1 product) (Huete et al., 1999). Nevertheless, if the composite period is too long, the land surface does not remain static; and if it is too short, the atmospheric disturbance cannot be removed effectively, especially in cloudy regions (Lu et al., 2007); consequently, there are some residual errors. For example, there exist many low quality pixels in 8- or 16-day composite MODIS products (Moody et al., 2005). Such noise degrades the data quality and introduces considerable uncertainty in temporal sequences, complicating the analysis of high temporal images sequences, as can be seen by drastically decreasing and/or increasing in the time series data. Therefore, noise reduction or fitting a model to observed data is necessary before temporal patterns can be determined (Sakamoto et al., 2005, Lu et al., 2007). The wavelet transform can decompose signals in time-frequency space in order to identify and reduce the overall noise as well as to maintain useful information in the time series data (Sakamoto et al., 2005).

The purpose of this study was to investigate the land use change based on the change of temporal patterns of the wavelet-filtered MODIS EVI. The consideration of temporal pattern analysis could also be used to support temporal pattern-based classification in the regional scale analysis.

2. METHODS

2.1 Study area

This study encompassed the island of Java which is located on the southern rim of Indonesia archipelago (upper left corner: 5°52'S 105°04'E; lower right corner: 8°47'S 114°36'E) and has an area of 132,792 km^2 (Figure 1). The climate of Java reflects the region's location in the tropics, with temperature and humidity remaining constant throughout the year, and rainfall varying between the seasons and the annual mean rainfall ranging from 1,000 mm up to 6,000 mm. From November until March, the zone of heavy rainfall covers most of Java, while from May until September; the zone of rainfall is limited to the southeast, leaving the eastern parts of island dry.

According to the BPS (2008), about 70.62% of Java is considered to be agricultural land use, as follows: paddy fields, mixed gardens, uplands/drylands, open grass, fishponds, state and private plantations, with as much as 5.43% of the area covered by settlements. On the other hand, Ministry of Public Works (2008) stated that paddy rice accounts for about 2,807,770 ha or 21.14% of Java's total area, while uplands/ drylands and non-irrigated areas cover about 6,352,850 ha or 47.84% of the total area. Forests in Java cover 22.98% of Java's area, consisting 1,246,728 ha of productive forest (9.39%), 550,849 ha of protected forest (4.15%), and 529,702 ha of conservation forest (3.99%).

2.2 Data

The MODIS LAND Discipline Group (MODLAND) (http://modis-land.gsfc.nasa.gov/vi.htm) developed the EVI for use with MODIS data following this equation:

$$EVI = G \frac{\rho^*_{nir} - \rho^*_{red}}{\rho^*_{nir} + C_1\rho^*_{red} - C_2\rho^*_{blue} + L}(1 + L) \qquad (1)$$

where, L is a soil adjustment factor, C_1 and C_2 describe the use of the blue band in correction of the red band for atmospheric aerosol scattering. The coefficients, C_1, C_2, and L, are empirically determined as 6.0, 7.5, and 1.0, respectively. G is a gain factor set to 2.5 (Huete et al., 1999). The MODIS EVI is embedded in the MODIS Terra Vegetation Indices (VI) Composite 16-day Global 250 m SIN Grid V005 or MOD13Q1 product.

In this study we used the MODIS EVI datasets which were acquired from February 2000 to December 2009 and captured 226 time series with interval time 16 days. The data were obtained at no cost from Land Processes Distributed Active Archive Center (LP DAAC), U.S. Geological Survey (https://lpdaac.usgs.gov/lpdaac/get_data/data_pool). The study area is covered by two MODIS tiles: h28v09 and h29v09. MODIS EVI data were extracted from the MODIS VI product (MOD13Q1) and the selected output format was GEOTIFF, which was then reprojected from Sinusoidal to Geographic system projection on datum World Geodetic System 1984 (WGS 84). The tiled MODIS EVI data were then mosaicked and clipped to cover Java for each composite period and then sequentially stacked to produce the time series dataset.

2.3 Land use change analysis

Land use change analysis based on the comparison of different dates independently does not allow recognizing the temporary and permanent changes within a land use type. Therefore, land use change detection discussed here is performed through detecting a change of the temporal pattern of vegetation index of successive years.

2.3.1 Image pre-processing using wavelet transform: The aims of image preprocessing are to improve the quality of the image and to produce an intermediate data set which will be used in further processing. As pointed out above, the MODIS EVI data products are still affected by bidirectional reflectance distribution factors or other residual noise, hence, we require a technique to reduce the impacts of noise on temporal data analysis.

The wavelet transform decomposes a signal into different scales by successively translating and convolving the elements of a high-pass and low-pass scaling filter associated with the mother wavelet. These filters retain the large- and small-scale components of the signals also known as the approximation (A) and detail (D) series, respectively. For most practical applications, the discrete wavelet transform (DWT), which analyzes signals over a discrete set of scales, follows a hierarchical algorithm for such decomposition, known as the pyramid algorithm.

In the first level of the decomposition, $f(t) = A_1 + D_1$, the signal has a low-pass filtered component, A_1, and a high-pass filtered component, D_1. In a second step, the approximation A_1 is split as $A_1 = A_2 + D_2$, and so on. The relationship $D_j = A_{j-1} - A_j$ gives us information about the portion of the signal that can be attributed to variations between the scales [j-1, j]. Figure 2 shows an example of such decomposition corresponding to the paddy field in Java Island.

In order to analyze the fluctuation of the EVI value of each land use type, we used the coiflet mother wavelet because this wavelet shape is as similar as possible to the patterns in agricultural phenology as pointed out by Sakamoto et al. (2005).

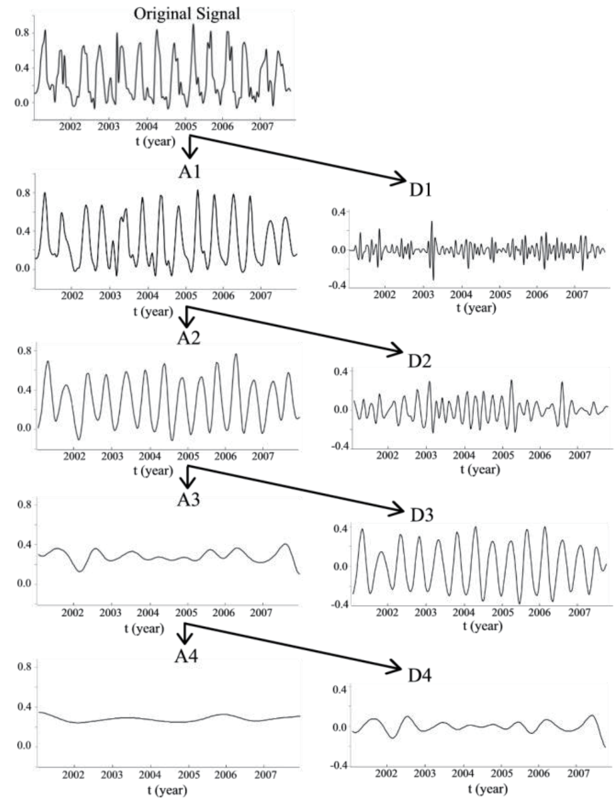


Figure 2. The structure of multilevel wavelet decomposition tree in the paddy field using the coiflet wavelet transform

The order in the wavelet function is a measure of the wavelet's smoothness, where a higher order produces a smoother wavelet. In this processing, the order 2 of the coiflet function was used since the trend of that order is similar to the trend of the original data. This analysis was performed using MATLAB through the 1-D multisignal wavelet analysis function. The MODIS EVI data pre-processing was conducted to provide a filtered data set to support multi-temporal (phenological analysis).

2.3.2 Land use change detection: The previous studies applied the temporal pattern change analysis to identify the land cover change, they are: change-vector analysis (CVA) (Lambin and Strahlers, 1994), standard normal distribution statistical analysis (Lunetta et al., 2006) and recursively merging algorithm (Boriah et al., 2008). In this study, the change area was assigned as a significant difference of the distances between each annual segment.

In the algorithm, any two successive annual segment may be merge into a new segment, $R_{new} = R_k \cup R_l$, furthermore, the distance function between segments has a form $d_{kl} = D(R_k, R_l) \geq 0$. Then, the segments merge with minimum distance as follows the function

$$d_{k,l} = \frac{N_k}{N_{new}} |\mu_k - \mu_{new}|^2 + \frac{N_l}{N_{new}} |\mu_l - \mu_{new}|^2 \quad (2)$$

where $d_{k,l}$ is distance between two successive segments, N is the number of observations, ($N_{new} = N_k + N_l$), and μ is a mean of segment ($\mu_{new} = \frac{N_k \mu_k + N_l \mu_l}{N_{new}}$).

Since the use of standard deviation (SD) as a threshold was difficult considering the possibility of the changed area in the study area and spatial resolution of the data, this study used a threshold which was represented by extreme values. The cumulative probability function (CPF) applied to determine distribution of extreme values. When the number of probability stagnant, it means that value is an extreme value of the data, and it will be used as a threshold level of the change criteria.

Moreover, in order to identify what kind of the change pattern occurred for each segment, those patterns were clustered into several types and then identified.

3. RESULTS

3.1 De-noising by Wavelet transforms

The result of filtering pattern of one pixel in agriculture area (example) and image pre-processing by using wavelet function are given in Figure 3 and 4, respectively. The figures show that wavelet transform filters some noises (de-noise) of MODIS EVI time-series data; so that the planting, heading and harvesting dates in the agricultural land especially can be determined.

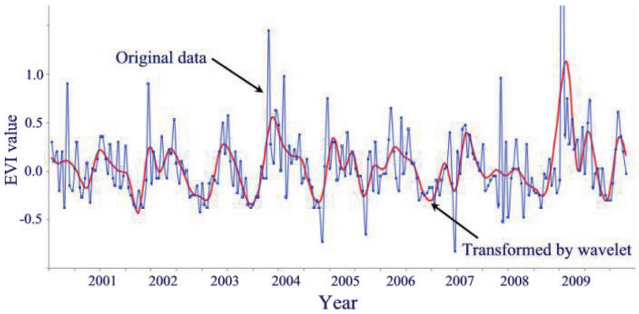


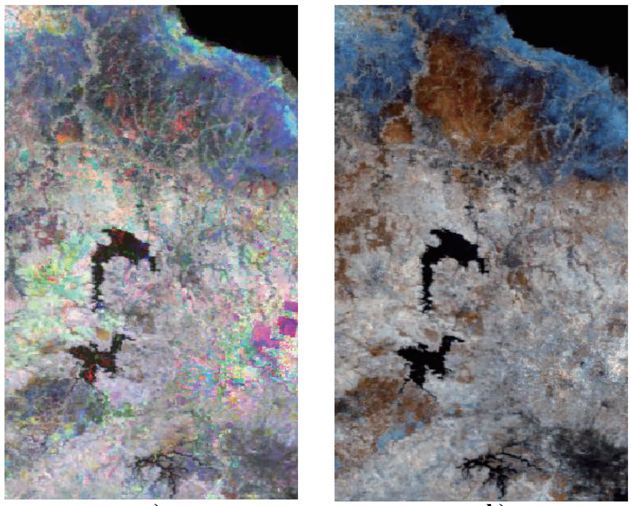
Figure 3. Filtering pattern of one pixel MODIS EVI by wavelet transforms

3.2 Land use change detection

Table 1 presents the change detection result and shows the largest number of change areas occurred in period 2004-2005 (452 locations) and 2005-2006 (412 locations). Meanwhile, distribution of these changed locations is given in Figure 5.

Table 1. The result of land use change detection

No	Period	Number of changed location	Changed area (ha)	Number of pattern type that contributed into LUC
1	2000-2001	125	1287.00	5
2	2001-2002	330	3793.75	8
3	2002-2003	28	1375.00	8
4	2003-2004	90	1975.00	8
5	2004-2005	452	5281.25	8
6	2005-2006	412	5268.75	8
7	2006-2007	224	2743.75	7
8	2007-2008	106	1268.75	9
9	2008-2009	91	1375.00	6



a) b)

Figure 4. a) image before transforms, and b) image after transforms.

Note: Images are displayed by combination of layer 5 (DOY2000_113), layer 4 (DOY2000_97) and layer 3 (DOY2000_81)

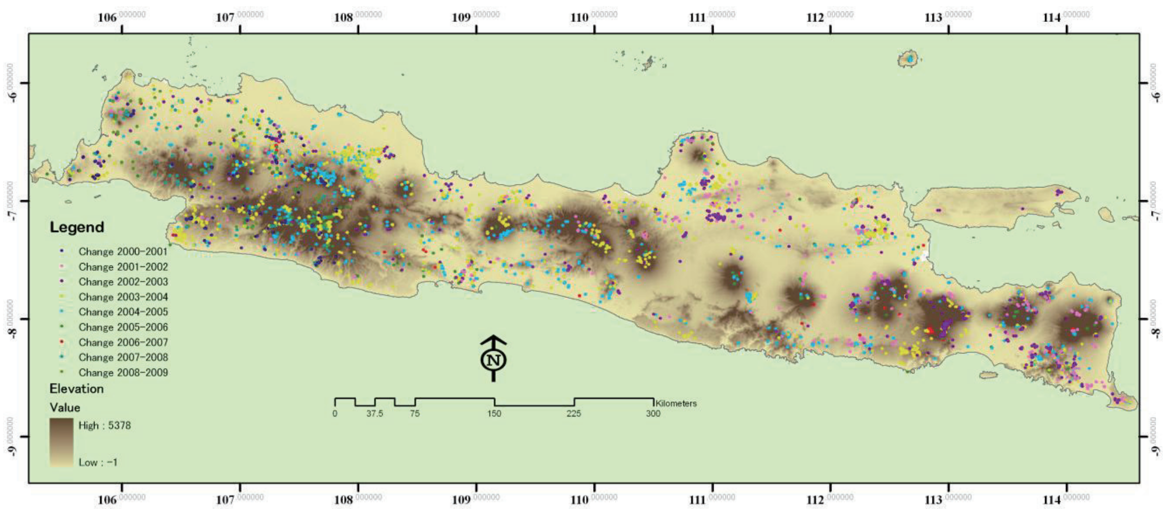
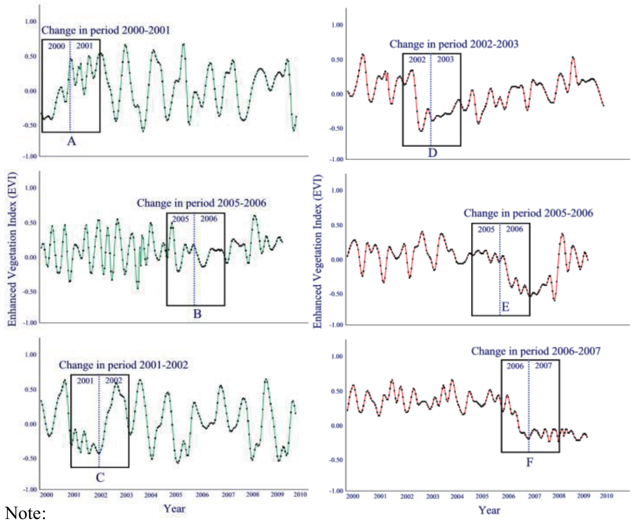


Figure 5. Distribution of land use change which can be detected by temporal pattern changed analysis

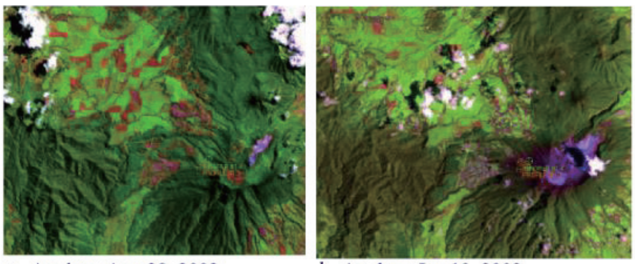
Regarding the clustering result of changed patterns, there are many significant trajectories/patterns contributed to cause an area is detected as a land use change per period as mentioned in Table 1. Moreover, Figure 6 displays some examples trajectory of EVI pattern which contributed to the area detected as land use change.



Note:

Type	Land use change trajectories which contributed to the LUCC
Pattern A	The area existed around a lake. In early 2000, that area was water, and after the water was drainage in the last 2000, then, in 2001, shrub grew up following seasonal event.
Pattern B	Some area of paddy field were converted into built-up (industrial facilities), even if there is paddy field around that area.
Pattern C	The area existed around a lake. When the water drainage, a shrub/ grass growth up in the area following seasonal event
Pattern D	Bush and mixed garden convert into barren land by volcanic activity (eruption) which occurred on November 2002. Hereafter the area was covered with sparse vegetation consisting of pioneer plants.
Pattern E	The conversion of mix garden and upland into barren land by the anthropogenic factors, it may be a part of plantation management.
Pattern F	Re-utilization of water storage which was covered by plants (eutrophication) for years. The plant was removed in 2007.

Figure 6. Some examples of significant patterns of EVI that contributed into the land use change



a Aq.date: Aug 28, 2002 b Aq.date: Jan 10, 2003

Figure 7. The event of land surface change by eruption (corresponds to the pattern D in Figure 6).

In addition, some locations have potentially to be changed several times in long term, from one land use type to another type and change again to others, and they could be identified by the changing of temporal pattern more than one times, as presented by Figure 8.

In Figure 8, pattern 1 is conversion of rubber plantation into teak plantations (*Tectona grandis sp.*) which combined with upland vegetation (Figure 9). Meanwhile, pattern 2 represents the changing of temporal pattern that occurred many times in paddy field. The extreme dry season in 2001 and 2007 caused the cropping system was changed; hence, that area was detected as the land use change in period 2000-2001, 2001-2002, 2006-2007 and 2007-2008.

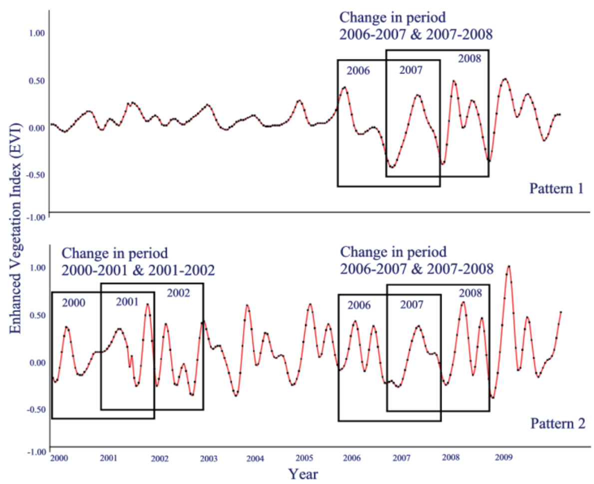


Figure 8. Two examples temporal patterns which have changed several times and contributed into the land use change

Figure 9. Teak plantation combined upland vegetation

Information which can be obtained by the temporal pattern analysis is also the land cover changed by the volcanic eruption (Figure 4, pattern D). Such kind of event occurred in West Java. Since the Mt. Papandayan erupted on November 12, 2002, many vegetation areas around the crater were covered by lava. This study also documented the impact of eruption on vegetation in Mt. Merapi, Central Java in 2006.

4. DISCUSSIONS

The wavelet-filtered MODIS EVI was used to detect the land use change due to the change of temporal pattern EVI. The change of temporal pattern EVI indicates the actual change of land use in study area.

Regarding the clustering of significant pattern, we identified several types of trajectories that contributed into the land use change (Table 1). In addition, as displayed by Figure 6, the change of temporal pattern EVI indicated the change of the surface. However, it may be contaminated by the extreme climate (e.g. impacted by El-Nino) as explained by Figure 8 (pattern 2). In tropical regions, the agricultural land depends on the water availability; so that, the cropping system follows the annual season. Therefore, detecting the changing due to comparison successive years becomes complicated when the annual dry season affects the change of cropping system. When the cropping systems changed, the temporal pattern also will be changed, and then, will be detected as land use change, even if, they were not.

In Figure 8 (pattern 2), the extreme dry season in 2001 and 2007 has caused the cropping system changed; hence, that area was detected as the LUCC in period 2000-2001 and 2006-2007. Moreover, the same area also was detected as the change area in period 2001-2002 and 2007-2008, however, both of the changes attributed by a reverse pattern of the previous period. The changed pattern was identified as the change area, even if they are temporarily changed.

Although the pattern analysis was concerned by the climate issues, but the approach is able to detect not only several trajectories/patterns of vegetated conversion, either one vegetation type converts into other vegetation type or non-vegetation area, but also identifying and monitoring re-vegetation process of non-vegetation area. Even if, those change areas may be lower than the area extent indicated in the field because of the inability of MODIS data to resolve an area less than 6.25 ha (250 m x 250 m).

The temporal pattern analysis of the MODIS EVI has a significant advantage for both capturing the actual timing of the change event and monitoring of the vegetation growth. However, such capabilities are limited by spatial resolution of the data. The use of multi-temporal data sets will be necessary to develop methodologies that utilize information on inter-annual variations to increase the accuracy of the land surface characterization.

5. CONCLUSION

This study applied the MODIS EVI to detect the land use change due to the change of temporal pattern. Meanwhile, the wavelet transform was applied into MODIS EVI to filter out some noises. The MODIS EVI wavelet-filtered could determine the planting, heading and harvesting dates in many vegetated lands, especially agricultural land. And, since the temporal dynamics of the land surface can be recognized by the temporal pattern, consequently, its changing also indicates the change of land use.

Analysis of temporal pattern is able to detect the land use change in Java. However, the significant change of temporal pattern still included the phenological phenomena or temporarily changed caused by the climate pattern. The extreme dry season, as an impact of climate pattern "El-Nino", changed the cropping system of agriculture land, then; it was detected as the land use change, even if they were not actually changed.

Considering to the effect of the extreme dry season, the use of segmenting two successive years as a segment is not appropriate to detect the land use conversion. Therefore, the segmentation should be extended more than two years in the further study.

6. REFERENCES

Ardli, E.R and Wolff, M. 2008. Land use and land cover change affecting habitat distribution in the Segara Anakan lagoon, Java, Indonesia. Regional Environmental Change 9 (4), pp. 235-243.

Boriah, S., Kumar, V. Steinbach, M., Potter, C., Klooster, S. 2008. Land cover change detection: a case study. Proceeding of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 857-865. Association for Computing Machinery

BPS, 2008. Statistics Indonesia. Badan Pusat Statistik, Indonesia. Project Supported by the Australian International Development Assistance Program-AusAID.

DeFries, R. S., & Townshend, J. R. G. 1994. NDVI-derived land cover classifications at a global scale. International Journal of Remote Sensing, 15, pp. 3567 - 3586.

Huete, A. R., Justice, C., & van Leeuwen, W. (1999). MODIS Vegetation Index (MOD13). Algorithm Theoretical Basis Document (ATBD) version 3.

Lambin, E.F., Strahler, A.H., 1994. Change vector analysis in multitemporal space: a tool to detect and categorize land cover change processes using high temporal resolution satellite data. Remote Sensing of Environment 48 (2), pp. 231–244.

Lambin, E. F., Baulies, X., Bockstael, N., Fischer, G., Krug, T., Leemans, R., Moran, E. F., Rindfuss, R. R., Sato, Y., Skole, D., II, B. L. T., & Vogel, C. 1999. Land-Use and Land-Cover Change (LUCC): Implementation Strategy. IGBP Report 48, IHDP Report 10, International Geosphere-Biosphere Programme (SC-IGBP) and the International Human Dimensions Programme on Global Environmental Change (SC-IHDP), Stockholm Bonn.

Lambin, E. F., Geist, H., & Rindfuss, R. R. 2006. Introduction: local processes with global impact. In E. F. Lambin, & H. Geist (Eds.), Land-Use and Land-Cover Change: Local Processes and Global Impacts, pp. 1 - 8. Germany: Springer-Verlag Berlin Heidelberg.

Lu, X., Liu, R., & Liang, S. 2007. Removal of noise by wavelet method to generate high quality temporal data of terrestrial MODIS products. Photogrammetric Engineering and Remote Sensing, 73 (10), pp. 1129 - 1139.

Lunetta, R. S., J. F. Knight, J. Ediriwickrema, J. G. Lyon, L. D. Worthy. 2006. Land-cover change detection using multi-temporal MODIS NDVI data. Remote Sensing of Environment, 105, pp. 142-154.

Ministry of Public Works. 2008. Research Institute for Water Resources Development. Ministry of Public Works, Republic of Indonesia.

Moody, E. G., King, M. D., Platnick, S., Schaaf, C. B., & Gao, F. (2005). Spatially complete global spectral surface albedos: Value-added datasets derived from Terra MODIS land products. IEEE Transactions on Geoscience and Remote Sensing, 43, pp. 144 - 158.

Prasetyo, L. B., Kartodihardjo, H., Adiwibowo, S., Setiawan, Y., Okarda, B. 2009. Spatial model approach on deforestation of Java Island, Indonesia. Journal of Integrated Field Science 6, pp. 37 – 44.

Runtunuwu, E. H. Pawitan,(2008). Hydrometeorological monitoring network of Java Island and hydrologic characteristics of the major river basins. JSPS-DGHE Joint Research Project, Tsukuba, October 2007.

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N., & Ohno, H. 2005. A crop phenology detection method using time-series MODIS data. Remote Sensing of Environment, 96 (3-4), pp. 366 - 374.

Verburg, P. H., A. Veldkamp and J. Bouma. 1999. Land use under condition of high population pressure: the case of Java. Global Environmental Change 9, pp. 303-312.